



## Kinematic Mobile Drop Jump Analysis at Different Heights Based on a Smartphone Inertial Sensor

by

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*The purpose of this study was to describe the acceleration variables in a plyometric jump test using the inertial sensor built into an iPhone 4S® smartphone, and the jumping variables from a contact mat. A cross-sectional study was conducted involving 16 healthy young adults. Linear acceleration, flight time, contact time and jump height were measured in a drop jump test from 60 cm and from 30 cm. Greater acceleration values were found in the drop jump test from 60 cm; the same was observed for the values from the contact mat. Multiple regression analysis was performed for each drop jump test: jump height was used as the dependent variable, and the most relevant variables were used as predictor variables (weight and maximum angular velocity in the Y axis for analysis of the drop jump from 60 cm, and weight and maximum acceleration in the Z axis for the drop jump from 30 cm). We found a significant regression model for the drop jump test from 60 cm ( $R^2 = 0.515$ ,  $p < 0.001$ ) and for the test from 30 cm ( $R^2 = 0.460$ ,  $p < 0.01$ ). According to the results obtained in this study, the built-in iPhone 4S® inertial sensor is able to measure acceleration for healthy young adults performing a vertical drop jump test. The acceleration kinematic variables are higher in the drop jump test from 60 cm than from 30 cm.*

**Key words:** acceleration, biomechanics, physical performance, plyometric training.

### Introduction

Plyometric training is commonly used to improve athletic ability. Plyometric exercises use the stretch shortening cycle, whereby muscles previously stretched are strongly contracted, allowing for the development of greater strength and power levels. One of the plyometric exercises commonly used is the drop jump (DJ), whereby the athlete performs a maximum vertical jump after falling from a specific height. The ability to perform jumps immediately after landing is especially important in assessing and predicting performance of athletes from different disciplines (Sawyer et al., 2002). In addition, vertical jump tests serve to evaluate anaerobic capacity, motor

development and athletic ability in sports (Rouis et al., 2015) and to detect neuromuscular fatigue (Gathercole et al., 2015). Specifically, performance in the DJ test has been related to sprint ability (Barr and Nolte, 2011), and the contact time achieved in DJ tests can be used to identify athletic talent (Bosco et al., 1983).

To assess vertical jump ability and progress in different plyometric jump training scenarios, the following validated tools are used: force platforms, video analysis systems, photocells and contact mats. These methods have shown high validity in the laboratory (Aragón, 2000). However, these motion measurement methods are costly; therefore, new tools for

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human motion analysis, such as inertial sensors, have been studied in recent years (Cuesta-Vargas et al., 2010), and accelerometer-based tools in particular have been validated for vertical jump assessment (Casartelli et al., 2010; Choukou et al., 2014).

In this way, inertial sensor units account for the possibility of landing outside of a predefined place as opposed to traditional ground-located force plates. This enables more functional and unplanned movement analysis in the training field itself (Dowling et al., 2011). A neutral pelvis position in the frontal and transverse planes is considered an important indicator of movement quality (Chmielewski et al., 2007; Whatman et al., 2013). A previous review (Reiman et al., 2009) showed that, given the importance of a good pelvic and knee position, further development of clinically applicable techniques for identifying athletes with poor alignment is needed. Identification of poor frontal plane pelvis, hip and knee control is considered an important factor in jump performance and the risk of suffering an injury (Whatman et al., 2013).

Currently, the latest generation of smartphones usually include among their specifications inertial sensors with subunits such as accelerometers and gyroscopes that can detect acceleration and inclination of devices. Numerous applications that display, store and transfer inertial sensor data have been developed for different smartphone operating systems. These applications have great potential for tracking human motion variables for research and clinical practice. Smartphones are beginning to be used as tools for analysing movement because of their low cost, easy accessibility and small size for multiple applications such as quantifying human motion (Nishiguchi et al., 2012) and physical characteristics (Galán-Mercant and Cuesta-Vargas, 2013), identifying and quantifying physical activity (Wu et al., 2012), fall detection (Mellone et al., 2012), functional tests (Galán-Mercant et al., 2014) and range of motion measurements (Ockendon and Gilbert, 2012). In a study in 2015, a smartphone application was validated for vertical jump assessment using the smartphone camera, however, no sensors were used (Balsalobre-Fernández et al., 2015).

In this context, the purposes of the present study were (1) to identify the kinematic

description of trunk acceleration and angular velocity in a cohort of young healthy people who performed a plyometric DJ test using the inertial sensor built into the iPhone 4S, and (2) to determine if the data provided by an inertial sensor unit from a smartphone placed at the lumbar spine could be related to anthropometrics and jump performance measured with a contact mat in simple and multivariate analysis. For these purposes, we measured trunk acceleration and angular velocity with the smartphone's inertial sensor in order to explore the associations of these variables with the data obtained with a contact mat.

## Methods

### *Participants*

This cross-sectional study was designed to examine the relationship between jump variables from a contact mat and kinematic variables from the inertial sensor built into a smartphone, in a plyometric jump test (DJ) from two different heights.

The study was approved by the ethics committee of the University of Málaga and complied with the principles laid out in the Declaration of Helsinki. Inclusion criteria were: students in health sciences from the University of Málaga, aged 18–35 years, free of diseases that could interfere with the performance of the tests. Furthermore, none of the participants were suffering from any joint or muscle pain at the moment of the study. Potential participants with a previous background of any severe injury of the lower limbs were excluded from this study.

### *Measures*

#### *Anthropometry*

Participants were weighed while barefoot and in underwear. Participants' height was taken as the distance from the vertex to the soles of the feet. It was measured with the participants in an anatomical position and with the occipital region, back, gluteal region and heels in contact with a height rod. Participants took a deep breath at the time of measurement. The body mass index (BMI) was calculated by dividing weight in kilograms (kg) by height in metres squared (m<sup>2</sup>). This procedure was performed following the guidelines of the International Society for the Advancement of Kinanthropometry (ISAK) (Ross et al., 1978).

### *Jumping performance*

The study protocol for jump assessment consisted of three trials of the DJ test described by Bosco et al. (1983) from a height of 30 (DJ30) and 60 cm (DJ60). Using a cycle ergometer, participants performed a 10 min warm-up before the jump and strength tests. Each participant was instructed on the proper way to perform the tests, and a jump trial was performed to verify it. Participants were instructed to drop from a step onto the contact mat and, with minimum contact time with the mat, attempt a maximum vertical jump. The instructions were: "Drop down and with minimum contact with the mat, jump quickly and try to achieve the maximum height possible". From the take-off phase to the landing of the jump, hip extension, knee extension and ankle plantar flexion had to be maintained. If the examiner detected any failure in performing the test, it had to be repeated. Jump height (cm), flight time (s) and contact time (s) in the DJ test were obtained using a Globus Ergojump Thesys® contact mat which had been validated previously (García-López et al., 2005).

### *Kinematic data*

Kinematic variables were obtained using an iPhone 4S® smartphone, which incorporates a three-axis gyroscope, accelerometer and magnetometer. The smartphone's accelerometer was used to determine acceleration, and the three-axis gyroscope to determine angular velocity. Inertial sensors built into the iPhone were accurate and reliable for measuring and quantifying physical activity in the laboratory setting according to a previous study (Galán-Mercant et al., 2014). The smartphone was fixed at L5-S1 level attached to a belt. The orientation and movement of the sensors are presented in Figure 1. The phone screen was facing backward. Linear acceleration along three orthogonal axes and angular velocity were saved with the application xSensor® Pro (Crossbow Technology, Inc.®). The data sampling rate was set to 32 Hz. A previous study (Galán-Mercant et al., 2014) showed that the cell phone (iPhone) accelerometer was accurate and precise enough to evaluate acceleration patterns in a mobility test compared to a gold standard, with an intra-class correlation coefficient of between 0.819 and 0.987. The data obtained in DJ tests were sent by email for offline analysis. We analysed raw data from the

smartphone application, which used a digital filter (Butterworth second-order filter). The maximum and minimum peak of acceleration and angular velocity in the three axes of movement (x, y and z), and the maximum and minimum peak from the resultant vector (RV) of acceleration [ $RV = \sqrt{x^2 + y^2 + z^2}$ ] were analysed as kinematic variables.

### *Statistical Analysis*

A database was created from the anthropometric data obtained from participants, the smartphone inertial sensor variables and the contact mat variables. Descriptive statistics were analysed with measures of the central tendency and dispersion of the variables. Inferential statistics were analysed using Pearson correlation coefficients and multiple regression analysis. The level of significance was set at  $p \leq 0.05$ . Statistical analysis was performed with SPSS® Statistics version 21 (IBM® software) for Mac OS®.

## **Results**

A total of 16 healthy adults (mean [SD]: height = 1.73 [10.66] m; body mass = 71.85 [14.46] kg; age = 25.50 [4.26] years; BMI = 23.74 [2.55]) signed an informed consent form to participate in the study. Table 1 shows the acceleration-based measures on the x, y and z axes and the contact mat measures for the DJ30 and DJ60 jump tests.

Table 1 shows that the height and flight time were greater for the DJ60 jump test. This difference was maintained in the acceleration results. For the RV results, higher values were obtained for the DJ60 jump test; the same was observed for the values from the contact mat (Table 1).

Figure 2 shows a graphical example of a DJ test; images of a participant during the sub-phases in the DJ test are shown as well as graphical sub-phase identification for the RV accelerations. Raw data and data with a low-pass filter are represented. We identified four sub-phases: A) first landing; B) contact time; C) flight; and D) second landing.

Results from the inertial sensor embedded in the smartphone demonstrated a correlation with those from the jump mat across the DJ tests analysed. In this way, significant correlations were found when accelerometry and jump mat data were compared (Table 2).

**Table 1***Acceleration-based and jump test values from a contact mat for DJ30 and DJ60 jump tests (n = 16)*

	Mean $\pm$ SD DJ30	Mean $\pm$ SD DJ60
<b>Accelerometer</b>		
Max acc X (m/s <sup>2</sup> )	7.848 $\pm$ 5.386	7.819 $\pm$ 5.376
Min acc X (m/s <sup>2</sup> )	-9.064 $\pm$ 5.788	-9.898 $\pm$ 6.200
Max acc Y (m/s <sup>2</sup> )	17.118 $\pm$ 7.053	19.296 $\pm$ 7.897
Min acc Y (m/s <sup>2</sup> )	-10.085 $\pm$ 3.169	-10.232 $\pm$ 3.247
Max acc Z (m/s <sup>2</sup> )	8.025 $\pm$ 4.473	8.407 $\pm$ 4.218
Min acc Z (m/s <sup>2</sup> )	-13.567 $\pm$ 5.768	-14.234 $\pm$ 5.386
Max acc RV (m/s <sup>2</sup> )	20.856 $\pm$ 7.142	23.024 $\pm$ 8.005
Max AngVeloc X (°/s)	2.989 $\pm$ 1.702	2.860 $\pm$ 1.817
Min AngVeloc X (°/s)	-2.847 $\pm$ 1.616	-2.963 $\pm$ 1.473
Max AngVeloc Y (°/s)	1.267 $\pm$ 0.660	1.533 $\pm$ 0.715
Min AngVeloc Y (°/s)	-1.493 $\pm$ 0.807	-1.437 $\pm$ 0.722
Max AngVeloc Z (°/s)	0.819 $\pm$ 0.382	1.028 $\pm$ 0.713
Min AngVeloc Z (°/s)	-0.917 $\pm$ 0.554	-1.044 $\pm$ 0.501
<b>Jump test mat</b>		
ump height (m)	0.287 $\pm$ 0.083	0.292 $\pm$ 0.087
Jump time (s)	0.479 $\pm$ 0.071	0.483 $\pm$ 0.074
Jump contact time (s)	0.342 $\pm$ 0.092	0.367 $\pm$ 0.088

*SD, standard deviation; DJ, drop jump test; max, maximum; min, minimum; RV, resultant vector; s, second; acc, acceleration; AngVeloc, angular velocity; m, metres; X, x axis; Y, y axis; Z, z axis*

**Table 2***Pearson correlation coefficient (n = 16)*

Correlated variables	Pearson r	p
Jump height DJ30 – max acceleration Z DJ30	0.374	0.009
Jump time DJ30 – max acceleration Z DJ30	0.373	0.009
Jump contact time DJ30 – min acceleration RV DJ30	-0.390	0.006
Jump height DJ60 – max AngVeloc Y DJ60	-0.337	0.019
Jump time DJ60 – max AngVeloc Y DJ60	-0.345	0.016
Jump contact time DJ60 – min acceleration RV DJ60	-0.342	0.017

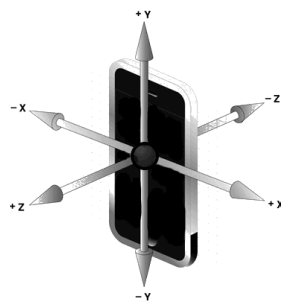
*Max, maximum; min, minimum; RV, resultant vector; X, x axis; Y, y axis; Z, z axis; DJ, drop jump test*

**Table 3**

*Multiple regression analysis (n = 16)*

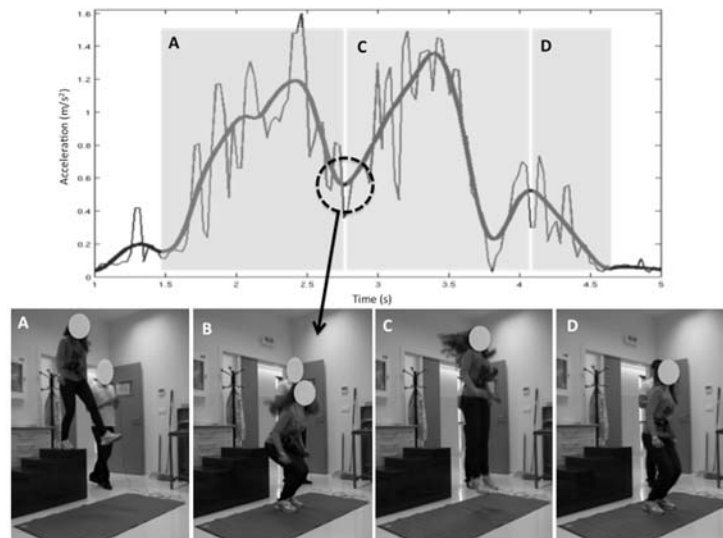
Dependent variable	Predictor variables	Standardised $\beta$	R2
Jump height DJ60	Weight	0.002++	0.515**
	Max AngVeloc Y DJ60	-0.037++	
Jump height DJ30	Weight	0.061†	0.460*
	Max acceleration Z DJ30	0.001++	

\* =  $p < 0.01$ ; \*\* =  $p < 0.001$ , significant R2 to the model. † =  $p < 0.05$ ; ++ =  $p < 0.01$ , significant contribution to the model.



**Figure 1**

*Axis orientation in the mobile inertial sensor*



*A. Down phase; B. first contact phase; C. flight phase; D. second contact phase*

**Figure 2**

*Graphical example of sub-phase identification from the resultant vector acceleration data in one drop jump test*

Finally, two multiple regression analyses were performed using jump height in each test as the dependent variable, and the most relevant variables as predictor variables. We found a significant model for the DJ60 ( $p < 0.001$ ) and DJ30 tests ( $p < 0.01$ ). Details of the models are presented in Table 3.

## Discussion

In this work, the inertial sensor built into an iPhone 4S smartphone was used to describe the acceleration variables in the three planes of motion in a plyometric jump test, and a contact mat was used to record flight time, contact time and jump height. The results of DJ tests from a height of 30 and 60 cm across acceleration variables from the smartphone's inertial sensor have been described and analysed. From the results, we identified that vertical jump variables and jump performance related to height in the DJ30 and DJ60 tests could be explained and influenced by different directly measured kinematic variables and weight. The variables found were kinematic variables in different planes in the pelvis and trunk.

A neutral pelvic position is also considered an important indicator of movement quality (Chmielewski et al., 2007). Identification of movement in the pelvis during jumps is considered important. To the best of our knowledge, this is the first study where kinematic influence on DJ performance has been studied by measurement with an inertial sensor embedded in a smartphone. This device could possibly be used as a simple clinical test for the identification of poor motor control in the pelvis during a jump test.

A previous study (Whatman et al., 2013) that investigated the ability of physiotherapists to rate the knee and pelvic position in young athletes visually during lower extremity functional tests concluded that acceptable specificity was achieved for a faster DJ, but a slower DJ lacked sensitivity and was not rated as accurate or reliable. In this way, a previous study concluded that the inertial sensors built into the iPhone were accurate and reliable for measuring and quantifying physical activity in a laboratory setting (Galán-Mercant et al., 2014). New tools for human motion analysis, such as inertial sensors and accelerometers, have been studied in recent

years; they have been validated for vertical jump assessment (Casartelli et al., 2010; Choukou et al., 2014; Cuesta-Vargas et al., 2010; Dowling et al., 2011) and could provide an alternative method of support in clinical environments (complex movement clinical test, fast movement clinical test, inexperienced therapist, etc.).

The use of inertial sensor devices to assess the biomechanical variables of vertical jump tests has been reported in the literature (Bonnet et al., 2013; Requena et al., 2011; Rowlands and Stiles, 2012; Setuain et al., 2015). Previous studies have found significant correlations between the biomechanical variables of jumping measured by kinematics and force plate data (Bonnet et al., 2013; Requena et al., 2011; Rowlands and Stiles, 2012; Setuain et al., 2015).

Several authors have studied sagittal and frontal plane lower limb kinematics during DJs (Blackburn and Padua, 2009; Delahunt et al., 2012; Dowling et al., 2011; Kulas et al., 2012); however, multiplane kinematic examinations of these jumps in healthy subjects based on direct smartphone measurement have not been conducted. To the best of our knowledge, no previous studies have used a smartphone's inertial sensor to describe DJs using acceleration values. In previous studies, inertial sensors have been used as feedback during DJs to prevent knee injuries (Dowling et al., 2011) and to analyse differences between sports populations (Setuain et al., 2015), and several studies have used inertial sensors in vertical jump tests (Casartelli et al., 2010; Choukou et al., 2014). A previous study carried out with a smartphone analysed squat jump and countermovement jump tests (Mateos-Angulo et al., 2015). In other previous studies, a smartphone application was used to estimate jump height in vertical jump tests. However, it did not use the inertial sensor of the smartphone to analyse the jump; the phone camera was used instead (Balsalobre-Fernández et al., 2015; Gallardo-Fuentes et al., 2016).

The acceleration values obtained by the smartphone's inertial sensor had different means between the DJ tests from two different heights (DJ30 and DJ60). In addition, different mean values were observed between the DJ30 and DJ60 tests for jump measurements including flight time, jump height and contact time.

The jump measurement data showed little

difference between jump heights and flight times in the DJ30 and DJ60 tests, but for contact time values, differences could be observed for different drop heights. The DJ30 test showed shorter contact times than the DJ60 test. This finding is consistent with results obtained in the study of Ball et al. (2010) where longer contact times were obtained for DJs from lower heights, in that case longer for jumps from 40 and 20 cm than from those at 60 cm. In another study (Peng, 2011), contact time was found to be significantly longer for a DJ from a height of 60 cm than from 20, 30 and 40 cm.

The motion axis that shows higher values of acceleration is the Y axis. This is because the vertical jump test technique implies that body displacement must be produced on the Y axis; higher trunk accelerations occur by body displacement during the drop from the box and the next vertical take-off. In addition, greater accelerations were recorded by the smartphone's inertial sensor on the Y axis for the DJ60 than for the DJ30. These data are consistent with the higher average jump height obtained for the DJ60. Therefore, higher acceleration values on the Y axis for the DJ60 can be explained by a larger store of elastic energy in the leg extensor muscles when drop height is increased (Komi and Bosco, 1978). Furthermore, several studies have indicated that higher drop heights result in higher ground reaction force values (Peng, 2011; Walsh et al., 2004).

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A limitation of the present study is that a sampling frequency of 32 Hz was used; a higher sample rate could probably allow the acquisition of better results in the tests evaluated. However, a previous study showed that a sampling frequency of 20 Hz can be optimal for measuring human movement while maintaining the accuracy of the measurement devices (Khan et al., 2016).

According to the results obtained in this study, we conclude that the inertial sensor built into the iPhone 4S® is able to measure acceleration variables for a vertical DJ test in healthy young adults. Acceleration kinematic variables derived from the smartphone inertial sensor were higher in the DJ test from 60 cm than from 30 cm. Jump performance could be explained by trunk kinematics and weight in the DJ test, thus in further studies mobile applications could be developed as powerful tools to assess vertical jump tests. Variables derived from smartphone inertial sensors can be used to evaluate technique in the DJ test.

The inertial sensors built into the last generation of smartphones can provide very useful variables with practical applications. This study shows that smartphones can be a cost-effective tool to evaluate vertical jump tests using trunk acceleration and angular velocity or as feedback in training vertical jump capacity.

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