

AN AUTOMATED METHOD FOR THE ESTIMATE OF VERTICAL JUMP POWER THROUGH INERTIAL MEASUREMENT UNITS

Guido Mascia^{1,2}, Valentina Camomilla^{1,2}

University of Rome “Foro Italico”, Rome, Italy¹
Interuniversity Centre of Bioengineering of the Human Neuromusculoskeletal System, Rome, Italy²

Vertical jump performance analysis allows for assessing the ability of the lower limb to generate mechanical power. The analysis performed with inertial measurement units (IMUs) is affected by inertial effects of wobbling masses. To compensate for them, an automated method was developed to estimate peak and mean concentric power based on anthropometric and time-frequency features. IMU data of 47 countermovement- (CMJ) and 50 squat- jumps (SJ) performed by 17 participants were used. Force platform data were used to obtain reference power values. Features were chosen according to the best subset regression method, devising a multiple linear regression for each estimated power parameter and jump. The regressions explained 88% and 96% variation, for CMJ peak and average power respectively, while explaining 75% and 74% of the variation for the SJ.

KEYWORDS: wearable sensors, countermovement jump, performance, feature selection.

INTRODUCTION: The vertical jump is a motor task often utilized for assessing the neuromuscular capacity of an individual. Countermovement jumps (CMJ) and squat jumps (SJ) can be exploited to quantify the ability of the lower limb at generating mechanical power, highlighting both the muscular eccentric and concentric contributions during the jumps. Peak and mean concentric power generated during the propulsion phase of the jump describing the power generated by the homonymous muscular contraction of the lower limb extensor muscles, are considered of particular interest. The mechanical power is complementary to the estimate of the height reached by the jumper (Barker et al., 2018; Dowling & Vamos, 1993; Linthorne, 2021; Markovic et al., 2014).

The instantaneous mechanical power as well as the height can be easily computed using a force platform (FP). Such instrument represents the *gold standard* for the measure of the ground reaction force acting on the human body (Linthorne, 2001). The product of the vertical component of the ground reaction force and velocity represents the instantaneous power expressed by the jumper. However, FP instrumentation is costly, non-portable, and does not allow on-field analysis. In the last decades, inertial measurement units (IMUs) arose as a valuable alternative for human movement analysis. They are often composed of tri-axial elements, namely an accelerometer and a gyroscope, measuring the sum of the external accelerations acting on the device and its rate of change of orientation, respectively.

IMUs have been used to estimate jump height in several studies revised in (Camomilla et al., 2018), but only a few assessed power during vertical jumps (Rantalainen et al., 2020). Nonetheless, issues are present when using IMUs that may be critical for their use, such as improper sensor calibration and sensor positioning. Moreover, due to the intrinsic nature of the human body, an IMU is subject to the inertial effects of the masses it is attached to, whose wobbling superimposes on the sensor's measures. This aspect is part of a wider phenomenon known as soft tissue artefact (STA) (Camomilla et al., 2017). The major issue brought by STA is that there is no known digital filtering technique to remove it, as well as it is both subject- and task- dependent. Hence, the computation of jump height directly from the acceleration trace measured by an IMU is affected by the inertial effects of the wobbling masses, making it virtually impossible to distinguish both the take off and the landing instants correctly (Picerno et al., 2011). Given that the peak power occurs prior the actual take-off, such parameter can be hypothesized as less affected by inertial effects.

For this reason, this study aimed to, first, assess peak and mean concentric power using IMU data and, second, to devise different multiple linear regressions (MLRs) including anthropometric and time-frequency parameters potentially related to STA, to improve the IMU-based estimates of power parameters.

METHODS: Seventeen participants (11M, 6F; age: 26.8 ± 4.7 years; height: 1.73 ± 0.09 m; mass: 72.0 ± 13.6 kg) volunteered for the study. To each of them, four skinfold lengths were measured, namely biceps, triceps, sub-scapular, and superior-anterior iliac crest (B, T, S, and I, respectively). An IMU composed of a tri-axial accelerometer and gyroscope (OPAL™, APDM Inc., Portland, Oregon, USA; 128 sample/s; full scale range: $\pm 6g$; ± 2000 degree/s) was inserted into the pocket of an elastic belt, worn at the waist by each volunteer. The IMU was positioned in correspondence of the L5 vertebra to resemble the ideal human center of mass. The sensor was calibrated prior to each session according to the recommendations proposed in (Bergamini et al., 2014). Hence, volunteers performed 3 countermovement- and 3 squat-jumps on a FP (Bertec Corp., Washington, Ohio, USA; 1000 sample/s), trying to maintain their elbows at the waist height, so that the arm-swing effect was minimized. Incorrect trials were not considered. A total number of 47 CMJ and 50 SJ were then analyzed.

IMU data were aligned to the world reference frame as proposed in (Rantalainen et al., 2020) to remove the gravitational component from the acceleration trace, thus obtaining the vertical component of the sensor acceleration, $a(t)$. We computed power, P , as normalized to the body mass of each participant, using F , v , and m , for the FP data; a and v , for the IMU data:

$$P(t) = \frac{F(t)v(t)}{m} = a(t)v(t)$$

where $v(t)$ was computed through numerical integration of $a(t)$ from the start of the trunk bending to the take-off instant for both instruments, and m is the subject mass computed from the FP measure in the static phase.

The power trace prior of each jump was used to compute IMU-based concentric and eccentric power peak (P_c and P_e), as the maximum and minimum power value, respectively, mean concentric and eccentric power (\bar{P}_c and \bar{P}_e), as average of the positive and negative power portion, respectively. These values, along with the following set of four time or frequency features, were used as independent variables in MLRs to estimate power parameters compensated for inertial effects. Namely, we computed: i) the temporal distance between the occurrence of the minimum and maximum power, P_Δ ; ii-iv) three central frequencies extracted using variational mode decomposition (VMD) from $a(t)$ (Dragomiretskiy & Zosso, 2014): two mid-high frequency components (f_1 , f_2), referring to the inertial components linked with the wobbling masses; a low frequency (f_3), associated with the jump movement of the trunk assumed as rigid. The eccentric part of the power was considered in the CMJ analysis only.

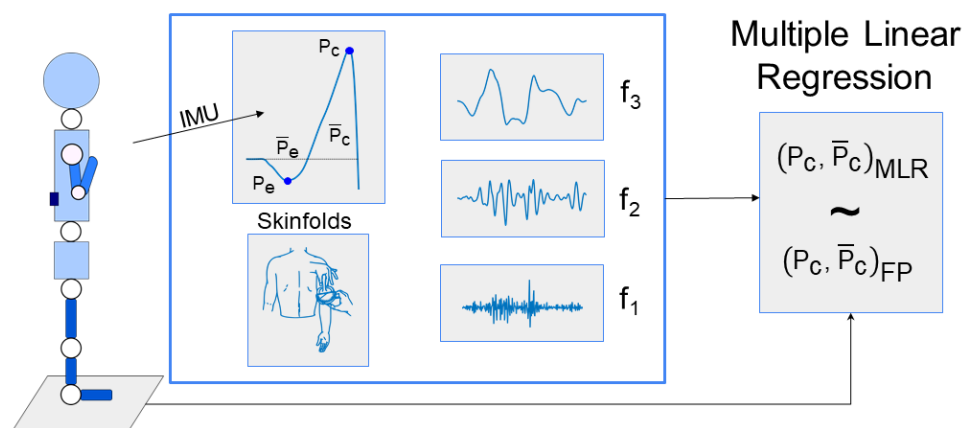


Figure 1: Schematic depiction of the utilized procedure for both P_c and \bar{P}_c estimation.

Four different MLRs were devised to provide corrected estimates of P_c (MLR^{P_c}) and \bar{P}_c ($MLR^{\bar{P}_c}$) for each jump, CMJ or SJ, indicated with a subscript. The feature set for each MLR was automatically chosen exploiting the best-subset regression method (Hocking & Leslie, 1967), coupled with a k-fold cross validation ($k = 10$) on the whole feature dataset. Hence, the best model was selected according to the lowest cross-validation error. The quality of estimates obtained using the raw IMU-data and of the MLR-corrected ones was assessed through mean average error (MAE) with respect to FP-derived reference power parameters. A schematic depiction of the procedure is presented in Figure 1.

RESULTS: The MAE of the peak concentric power, P_c , obtained from raw IMU data had MAE expressed in percentage of the FP-derived power parameters of $15.2 \pm 8.6\%$ and $12.7 \pm 8.4\%$, for CMJ and SJ, respectively. MLR analysis, reported in Table 2, improved this estimate reducing MAE% to $6.4 \pm 5.5\%$ and $8.5 \pm 7.8\%$, for CMJ and SJ, respectively. Similarly, mean concentric power, \bar{P}_c , obtained using IMUs had MAE% of $21.5 \pm 16.7\%$ and $19.3 \pm 13.9\%$, for CMJ and SJ, respectively. MLR analysis reduced MAE% to $6.0 \pm 5.6\%$ and $14.3 \pm 12.4\%$ for CMJ and SJ, respectively. The MLR models had slightly better performances for the CMJ, explaining the 88% and 96% variation, for P_c and \bar{P}_c respectively, while explaining 75% and 74% of the variation for the SJ. Absolute error values for all MAE are reported in Table 1, along with significance details.

Table 1: Reference power and mean average errors for IMU measures and MLR estimates (W / kg).

	FP reference	error IMU	error MLR	explain	R ²	F	p
P_c^{CMJ}	18.75 ± 4.73	2.82 ± 1.81	1.18 ± 0.98	88.4%	.894	$F(4, 44) = 90.52$	$< 10^{-16}$
\bar{P}_c^{CMJ}	7.17 ± 2.35	1.45 ± 1.12	0.36 ± 0.27	95.5%	.963	$F(8, 39) = 125.5$	$< 10^{-13}$
P_c^{SJ}	21.62 ± 5.25	2.81 ± 1.99	1.82 ± 1.66	75.2%	.777	$F(5, 44) = 30.66$	$< 10^{-16}$
\bar{P}_c^{SJ}	6.36 ± 2.21	1.24 ± 1.00	0.84 ± 0.69	73.8%	.754	$F(3, 46) = 46.99$	$< 10^{-14}$

Table 2: MLRs absolute (above) and standardized coefficients (below). Significance level: * p < 0.001; ** p < 0.01; * p < 0.05; § p < 0.1.**

	Const	P_c	\bar{P}_c	P_e	\bar{P}_e	B	T	S	I	P_Δ	f_1
$MLR_{CMJ}^{P_c}$	10.40***	.47***	.61***	-	-	-.24**	-	-	-.09§	-	-
$MLR_{CMJ}^{\bar{P}_c}$	9.20***	.16***	.2**	.14**	1.33***	-.10***	-.08**	-.11***	-	-8.91***	-
$MLR_{SJ}^{P_c}$	6.04	.69***	-			-	-	-.27§	.35**	-14.95*	.36*
$MLR_{SJ}^{\bar{P}_c}$.77	.25***	-			-	-	-	-	-7.02**	.18**
$MLR_{CMJ}^{P_c}$.49	.39	-	-	-.19	-	-	-.11	-	-
$MLR_{CMJ}^{\bar{P}_c}$.33	.22	.18	.28	-.16	-.14	-.23	-	-.36	-
$MLR_{SJ}^{P_c}$.81	-			-	-	-.25	.36	-.21	.19
$MLR_{SJ}^{\bar{P}_c}$.69	-			-	-	-	-	-.23	.23

DISCUSSION: The current study provides sports scientists with a practical and open method to correct for IMU-related errors in power computation during vertical jump. IMU intrinsic measurement errors showed to entail important inaccuracies in the estimate of jump power parameters. The best subset regression method here used, combining both anthropometric and time-frequency features, seems to be a promising approach to jump power

characterization. All devised MLRs reduced estimate errors in terms of MAE. Regressions developed for SJ, presenting slightly higher errors, suffered from a smaller number of available features due to the absence of an eccentric power component of the motor task. As regards regressions obtained for CMJ, both embedded anthropometric independent variables. With due caution, this could be explained by the fact that the inertial effects brought by wobbling masses, presumably described by skinfolds, were more impactful when the jumper executed a countermovement.

The study enrolled only healthy individuals with an amateur potential to express power. Further MLR estimates should be developed for elite athletes with different performance potential and anthropometry to grant for a more robust generalizability of the current MLRs. To complement power estimates, the proposed approach could be applied to jump height analysis with IMUs.

CONCLUSION: An automated method for correcting jump-generated power as measured by IMUs was presented. Results confirm that inertial effects had a negative effect on the quality of the power parameters computed directly through IMU measures. However, errors can be reduced by devising proper MLRs which consider anthropometric and time-frequency features. Further studies should focus on reducing the effect of STA affecting other jump-related quantities, such as height.

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