STANDING LONG JUMP POWER ESTIMATION FROM SMARTPHONE IMUs

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The purpose of this study was to provide athletes/coaches with an easy-to-implement estimate of the power of standing long jump (SLJ), recognized as an indicator of the ability of lower limbs of exert power. To this aim, inertial sensors embedded in smartphones were used. A sample group of 150 trained young participants was recruited and asked to perform the SLJ task while holding the smartphone. A set of features was identified, based on biomechanical knowledge and literature, and then selected through Lasso regression to be feed as input of three different optimized machine learning architectures to estimate the SLJ power. A Multi-Layer Perceptron Regressor was selected as best performing model and showed, in the test phase, a RMSE of 0.37 W/kg. This smartphone-based estimate, if compared to an average power of 1.8 W/kg, represents a reasonable approximation.

KEYWORDS: SLJ, inertial sensors, regression, machine learning, performance.

INTRODUCTION: The standing long jump (SLJ) is a sports-related movement widely used for several aims since it entails a dominant horizontal propulsion, often crucial in determining performance. Among those aims there is the assessment of anaerobic power (Almuzaini & Fleck, 2008; Mann et al., 2021). Despite its wide potential, all these studies were limited to the simple and ecological evaluation of the jumped distance (meter-based) and only few studies characterized the power of the jump using laboratory instrumentation (Harry et al., 2021; Hickox et al., 2016; Mackala et al., 2013; Szerdiová et al., 2012; Wu et al., 2012). Laboratory-based measures are not applicable in the field and require expert operators.
As an affordable and practical alternative to commercial inertial measurement units (IMUs) and laboratories, applications based on IMUs embedded in smartphones (SPs) are being developed to provide coaches with low-cost information on jump performance. These sensors were not developed specifically for biomechanical analysis, and do not always satisfy the required specifications, such as high sampling frequency or appropriate full-scale range. Nevertheless, useful information can be retrieved overcoming these drawbacks through predictive approaches. While machine learning (ML) was used to estimate SLJ length (De Lazzari et al., 2023), counter-movement jump (CMJ) height (Mascia et al., 2023) and power (White et al. 2022), for the estimate of SLJ power a stepwise multiple regression model predicting only total power based exclusively on anthropometric features and jumped length was proposed (Mann et al. 2021). Data from the jump execution and details along the anteroposterior (AP) direction are still lacking.
The aim of this work is to use IMUs embedded in smartphones to estimate the mean SLJ power along the AP direction considering an ML approach, that can be easy used and understood by trainers. To this aim, non-categorical biomechanical features related to the jump technique and intrinsic anthropometric characteristics are used as tools to train and test selected ML architectures, allowing interpretability of the proposed ML solution. Biomechanical variables were selected based on two assumptions: i) in the preparation phase, the SLJ vertical acceleration is similar to that expressed during a CMJ, since both jumps entail an eccentric and a concentric phase, although involving different muscles coordination; ii) in the flight phase, the origin of the sensor coordinate system follows a parabolic trajectory. Three ML models dedicated to regression analysis were selected, trained, optimized, and tested to this aim.

METHODS: One hundred fifty physically active healthy sports science students were recruited as participants (75M, 75F; mean ± SD: age = 22.3 ± 4.7 y; stature = 1.75 ± 0.12 m; mass =

67.7 ± 10.9 kg). Individuals who had undergone either lower limb surgery or an injury in the six months prior to the experiments were excluded from the study. All participants signed an informed consent prior to the tests. The study was approved by the Institutional Review Board. Participants were equipped with an SP held horizontal with the screen pointing laterally in their right hand (Samsung Galaxy S9+, Samsung Group, Seoul, South Korea; 500 samples/s; full scale range: ± 8g; ± 500 deg/s). SP-IMU data were collected using the app Phyphox (Staacks et al., 2018), remotely controlled through the laboratory PC. SP-IMU calibration was performed before each experimental session. Afterwards, each participant performed a series of 3 SLJ: i) keeping the upright position for 3 s with hands on the hips, feet in parallel stance, and heels positioned at the zero of a meter tape; ii) jump forward as triggered by a vocal command; iii) regain the upright static position and keep it for 3 s. The jump was considered correct if the participant kept the equilibrium after landing without additional steps, keeping the feet in the parallel stance position and the arms still. Jumps were executed with the left hand on the hip and the right one near to the hip while firmly holding still the SP, which was observed to undergo negligible rotation from onset to take-off. Participants jumped over a force plate (AMTI, Watertown, Massachusetts, USA; 1,000 samples/s; size= 40×40 cm) which allowed to calculate the gold-standard mean power in antero-posterior (AP) direction ($P_{AP,mean}$) using Newton's laws. Power was averaged from the jump onset to take-off. Onset was obtained as 30 ms prior deviating by 8 times the standard deviation of the static phase; take-off was obtained as the first frame such that $a_V \leq -g$.
Data preparation of the SP-IMUs considered the following steps: the calibration before each experimental session, the correction of their offset and cross-axis sensitivity according to (Bergamini et al., 2014) and a subsequent consistent gravity removal. Vertical (a_V) and anteroposterior (a_{AP}) acceleration components were expressed into a global coordinate system under the hypothesis that the SP was kept parallel to the plane of movement, i.e. without yaw corrections (Rantalainen et al., 2020), and then considered for further computations after a low-pass Butterworth filter at 50 Hz. Vertical (v_V) and anteroposterior (v_{AP}) velocities were calculated through the numerical integration of the corresponding acceleration signals from the onset to the take-off instants.
Sixty-one features were extracted including age, height, mass of the participant and jump length, measured as heel-to-heel distance. The remaining features were extracted from the preparation phase of the above-mentioned accelerations and velocities, further segmented into eccentric and the concentric subphases in accordance with (Harry et al., 2021; McMahon et al., 2018) and similarly to what used for the estimate SLJ length (De Lazzari et al., 2023).
A final dataset of 450 jumps x 61 features was made available to estimate the dependent variable: $P_{AP,mean}$ normalized with respect to the mass of the participant ($P_{ap,mean/mass}$). This dataset was divided into two subsets: 80% (120 subjects, 60 M and 60 F, 360 jumps) was used as training set, the remaining 20% (30 subjects, 15 M and 15 F, for a total of 90 jumps) was used as test set. This separation was entrusted to a randomization algorithm that provided an equal distribution of both males and females in training and test sets. The independency of the subsets was granted by allocating examples belonging to the same subject to the same subset. Feature reduction was performed through Lasso regularization on the normalized training set with $\alpha = 0.1$ as regularization strength value, to avoid possible multicollinearity among features (Tibshirani, 1996). Only the features selected by such a shrinkage were used to develop the ML model and imported into JupyterLab for model development.
The following regressive models were tested, using the related Python functions: RandomForestRegressor (RFR), chosen because it's a simple network that could be implemented in a smartphone application; GaussianProcessRegressor (GPR) and MLPRegressor (MLPR), chosen as former good solutions to similar problems (De Lazzari et al., 2023; Mascia et al., 2023). The three networks were optimized by grid search hyperparameter optimization algorithm. To avoid leakage of data and have a robust optimized model: (i) the GroupKFold (with K=5) cross-validation was applied during the grid search to guarantee the separation of subjects in the folds and (ii) the PowerTransformer function was used inside GridSearchCV to correctly normalize every time the subsets in the fold. The hyperparameters optimised through GridSearchCV are reported in Table 1.

The best hyperparameters were selected using the mean absolute error as criterion. The test set was normalized with respect to the values of the training set and then used to make predictions. Metrics used to assess the quality of the model were: mean squared error (MSE), root mean squared error (RMSE), mean absolute error (MAE) and R^2.

Table 1: Screened and optimal values for the selected hyperparameters in GridSearchCV for RandomForestRegressor (RFR), GaussianProcessRegressor (GPR), MLPRegressor (MLPR).

Regressor	Hyperparameters	Screened Values	Optimal values
RFR	'max_features'	{'sqrt', 'log2', None}	None
	'n_estimators'	range(100,300)	230
	'criterion'	{'squared_error', 'absolute_error', 'friedman_mse', 'poisson'}	'poisson'
GPR	'kernel'	{RBF, RBF+Constant}	RBF+2**1
	'alpha'	range(10^{-13},1^{-9})	10^{-10}
	'optimizer'	{'fmin_l_bfgs_b', None}	'fmin_l_bfgs_b'
MLPR	'activation'	{'identity', 'logistic', 'tanh', 'relu'}	'identity'
	'alpha'	range(10^{-8},10^{-3})	10^{-6}
	'learning_rate'	{'constant','adaptive','invscaling'}	'invscaling'
	'solver'	{'adam', 'sgd'}	'adam'
	'hidden_layer_sizes'	one hidden layer with units with range(1,50)	49

RESULTS AND DISCUSSION: $P_{ap,mean/mass}$ of the 450 analysed jumps (1.8 ± 0.7 W/kg) ranged from a minimum of 0.34 W/kg to a maximum of 3.79 W/kg, with a jumped distance (1.74 ± 0.33 m) ranging from 0.86 m to 2.6 m.

Fifty features out of 61 were selected by Lasso regularization, including the jump's length, most biomechanics features and all the anthropometric ones. They were used as input of the model. The optimized hyperparameters are reported in Table 1, while Table 2 summarises the performance of the tested models. Consistency between train and test phases of R^2 values, considered as most informative metric for regression models following (Chicco et al., 2021), show that both MLPR and RFR are more stable than GPR. Among the two, the MLPR was as selected as best performing model and showed, in the test phase, a RMSE of 0.37 W/kg. This smartphone-based estimate, if compared to an average power of 1.8 W/kg, represents a reasonable approximation.

Table 2: Metric values obtained during the cross-validation phase (the mean values over the folders are reported for each metric) and in the test phase of the three regression models.

Metric	$CV_{mean,RFR}$	$Test_{RFR}$	$CV_{mean,GPR}$	$Test_{GPR}$	$CV_{mean,MLPR}$	$Test_{MLPR}$
MSE [$(W/kg)^2$]	0.11	0.15	0.15	0.21	0.11	0.13
RMSE [W/kg]	0.33	0.39	0.39	0.46	0.33	0.37
MAE [W/kg]	0.26	0.32	0.30	0.37	0.26	0.31
R^2	0.72	0.72	0.64	0.62	0.74	0.74

The quality of the regressor cannot directly be compared to the single one available by Mann et al. (2021) which focused only on total power and on a more specific and smaller population, 58 football players from NCAA Division IA program. While total power remains to be assessed, it can in general be speculated that including biomechanical features as inputs to the model may lead to improved results.

The level of physical activity of the selected healthy sports science students ranged from recreational to National interest. This range was welcomed as an opportunity to develop a model to be applied in several contests. Indeed, based on the test R^2 values, the selected model can be applied to a wide range of jumped distances and related power. However, further analyses are warranted to test if the model could lead to improved estimates if developed separately for different jump lengths or athlete's expertise. Moreover, only ML regressors were included in this preliminary analysis. Improved results could be obtained with different architectures.

CONCLUSION: This study identified an opportunity to estimate the mean power along the direction of the jump out of the laboratory with an approach understandable by coaches and trainers. This solution could lay the basis for an improvement of the performance of athletes giving more information about the task, that could be implemented into a smartphone app: implementing this solution, an estimate of the power and a relation with key biomechanical features could be provided to coaches to improve performance.

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