An Accelerometer-Based Training Load Analysis to Assess Volleyball Performance.

Case Study

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Abstract

Introduction: The purpose was to quantify a volleyball athlete's accelerometer-based workloads and utilize a neuromuscular fatigue jump test to assess on-court performance throughout a competitive season.

Methods: One, Division I volleyball athlete was monitored throughout each practice and competitive game using a validated wearable microsensor device (Catapult Sports). To assess neuromuscular fatigue, an approach jump (AJ) test was completed weekly. On-court statistics were recorded each game.

Results: Utilizing a forward linear regression model, low intensity decelerations, moderate and high intensity accelerations, and low and high intensity jumps accounted for 91.7% of the variation in weekly relative power assessed via AJ test ($p < 0.001$). Of those variables, only high intensity jumps were significantly ($p = 0.035$) different between practices that occurred prior to winning (49.6 ± 26.7) and losing (69.2 ± 39.8) game performances. Additionally, hitting percent was significantly better ($.266 \pm .190$ win; $.130 \pm .129$ loss; $p = 0.05$) in winning performances.

Conclusions: Alterations in approach jump performance throughout a competitive season is multifaceted; however, limiting high intensity jumps in practice may be advantageous to optimize volleyball performance.

Key Words: Regression, monitoring, jump loads, wearable data

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Introduction

Volleyball is an interval sport that requires repetitive high intensity jumps to successfully compete at an elite level [1,2]. Monitoring jump loads in volleyball athletes is feasible with the utilization of wearable microsensor technology [3,4]. Much of the research utilizing this technology has reported its effectiveness to quantify movements and predict athletic injuries [2,3,5,6]. However, there is a lack of research demonstrating how wearable data can be analyzed with a separate fatigue assessment (e.g., approach jump (AJ) test) to potentially improve the periodization of practice training loads (e.g., high intensity jump counts). Therefore, the purpose of the study was to monitor a Division I volleyball athlete

with a wearable device for an entire season, assess weekly neuromuscular fatigue, and predict which external loads (e.g., accelerations, decelerations, and jumps) contribute to neuromuscular fatigue and on-court performance.

Methods
Participant
One Division I female volleyball athlete (outside hitter, 20.5 years old) that did not substitute out of any match was monitored throughout a competitive season.

Protocol
Prior to each practice and game, a wearable microsensor device was secured to the upper back and the device utilized a 100Hz gyroscope, magnetometer, and tri-axial-accelerometer using the gravity corrected inertial movement analysis technology (Catapult Sports, Melbourne Australia). The athlete was cleared by the team physician, read and signed an informed consent form and gave informed consent. The athlete's weight, standing reach height and best of three AJs were measured before the season. Measurements continued on a weekly basis, 48-hours after a competitive game. The university Institutional Review Board approved the study. Neuromuscular fatigue was assessed via the AJ test (3-4 steps prior to a maximum effort jump) [7,8] and the highest of three attempted jumps was recorded. The results for the jump tests were calculated using the following equation, highest jump height (cm) – standing reach height (cm) = AJ height (cm). After all jumps were completed, the athlete's power (Watts) was calculated using the validated Sayers equation (60.7 * Height (cm) + 45.3*BW (kg) – 2055) and then relative AJ power (Watts/kg) was calculated (Power in Watts/BW (kg)) [9].

Data Analysis
A total of 83 data sessions were downloaded utilizing the OpenField software (Catapult Sports, Melbourne Australia). External load data and on-court performance statistics (e.g., hitting percent, blocks, kills and digs) were classified based on games won and lost. Practice load data was also coded in to four different training days (e.g., one, two, three, and four days prior to winning and losing competitions). External loads were recorded according to the default setting by the device manufacturer. Most importantly, low, moderate and high intensity jumps were defined as 0-20 cm, 20-40 cm, and >40 cm, respectively. On-court statistics were reported throughout each game by an official scorekeeper for each game.

Statistical Analysis
Descriptive statistics (means and standard deviations) for all external load variables were calculated for winning and losing practices/games and for practices that occurred one, two, three and four days prior to winning and losing competitions. Practices that occurred prior to a winning or a losing game are termed in the study as winning practice and losing practice, respectively. A forward regression was utilized to predict if any external load variables (independent variables) accounted for variations in relative AJ power (dependent variable) throughout the season [10]. Independent t-tests were utilized to compare external load data and on-court performance statistics between winning and losing practices and games. Statistics were analyzed using IBM SPSS 24.0 (Version 21.0, IBM Inc., Armonk, NY). The criterion for statistical significance was set a priori at $P \leq 0.05$.

Results
The athlete's pre-and post-season weight and jump performance is listed in Table 1.

Table 1. Pre-and post-season descriptives.

	Pre	Post	% Change
Weight (kg)	66.2	63.0	-4.8
AJ Relative Power (Watts/kg)	73.3	74.7	1.9
AJ Absolute Power (Watts)	4852.7	4670.0	-3.8
Maximal AJ Height (cm)	64.8	64.8	0.0

The forward regression analysis revealed that low intensity decelerations, medium and high intensity accelerations, and low and high intensity jumps, accounted for 91.7% of the variation in maximal relative approach jump performance ($r = .958$, $r^2 = .917$, $p < 0.001$). The t-tests comparing all external load variables and on-court statistics are shown in Table 2. There were significant ($p = 0.05$) differences in high intensity jumps two and four days before winning and losing performances (Figure 1). The athlete also had a better hitting percentage in winning performances, relative to losing performances ($p = 0.05$, Table 2).

Table 2. External loads based on winning and losing practices and games.

Practice (N = 56)	Win (n = 39)	Loss (n = 17)	Game (N = 27)	Win (n = 16)	Loss (n = 11)
Mod Accels	13.9 ± 7.7	18.5 ± 11.4	Mod Accels	22.2 ± 8.9	19.1 ± 5.4
High Accels	5.8 ± 3.5	8.6 ± 5.7	High Accels	7.9 ± 3.2	10.6 ± 5.3
Low Decels	59.4 ± 41.7	72.0 ± 41.1	Low Decels	72.9 ± 39.7	71.6 ± 36.5
Low Jumps	5.6 ± 5.1	5.9 ± 4.9	Low Jumps	8.7 ± 5.5	7.6 ± 4.1
High Jumps	49.6 ± 26.7[*]	69.2 ± 39.8[a]	High Jumps	44.0 ± 20.1	40.0 ± 14.4
-	-	-	Hitting %	.266 ± .190[b]	.130 ± .129
-	-	-	Kills	12.9 ± 5.8	9.8 ± 5.3
-	-	-	Digs	9.9 ± 5.7	10.3 ± 3.5
-	-	-	Errors	4.5 ± 2.3	5.5 ± 2.8

Data are Means ± Standard Deviation
[*] Significantly less than losing practices, $p = 0.035$.
[a] Significantly greater than games, $p < 0.028$.
[b] Significantly greater than losing games, $p = 0.05$.
Variables not indicated were not significant, $p \geq 0.15$ for all

Figure 1. Practice taper prior to winning and losing game performances

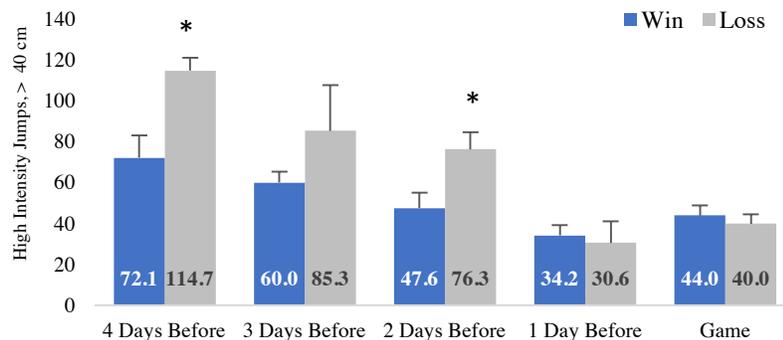

Figure 1 illustrates average high intensity jump counts four days prior to a winning and losing game performance.
*Significantly greater than games and winning practices two and four days before a game ($p \leq 0.05$).

Discussion
Excessive high intensity jumps in practice can potentially influence on-court volleyball performance. Only high intensity jumps, relative to all other external loads, were significantly different between practices prior to winning and losing performances. On average, the athlete engaged in 20 fewer high intensity jumps in practices prior to a winning performance and a further analysis revealed that the athlete accumulated an average of 28.7 and 42.6 fewer high intensity jumps two and four days prior to a winning performance, respectively. Interestingly, the athlete also had, on average, a 104% better hitting percentage in winning competitions. It is possible that, in part, fatigue from excessive high intensity jumps in practice contributed to decrements in on-court performance [11,12]. Previous research supports this explanation as neuromuscular fatigue has been found to negatively alter cognitive ability and on-court movements that lead to mistimed body and ball positioning errors [11,12]. In conclusion, excessive high intensity jumps in practice could induce fatigue and hamper performance. The findings highlight the need for individualized athlete analytics based on integrating wearable data, jump performance data, and on-court performance data.

Media-Friendly Summary
Limiting high intensity jump counts in practice by as few as 20 jumps per session may help reduce a volleyball athlete's fatigue and improve on-court hitting percentage.

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