Automated IMU-based training load monitoring in beach volleyball

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Initial situation and project goal

Optimize training and regeneration management

German Volleyball Association (DVV) ⟶ Need for research and development in the field of training documentation in beach volleyball, especially automated recording of training load

Due to the sandy ground surface and the structure of the game (3-contact rule, two persons per team), in beach volleyball, in addition to jumps, it is primarily short sprints, fast lateral movements, and dig movements with direct follow-up action that determine the degree of stress and load on the players (Pelzer et al., 2020).

(see also: BISp project AZ: ZMVI4-072023/18)

Identification of relevant loads

Training load: frequencies of basic techniques without jumping, jumping actions and defensive actions

Basic techniques (no jumps)	Jumps	Defensive actions
• Set / setting • Pass (forearm, bump) • Service	• Jump service (Float/Top spin) • Attack (Smash, Cut, Poke) • Block	• Reception / defense (one/two arms) • Sprints • Intensive defense (plus dig / sand contact)

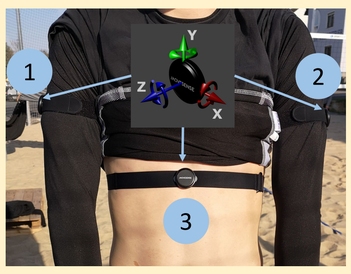
Aim of the project

Development of a practical, cost-effective system for the automated monitoring of training load in beach volleyball

Concept and study setting

Technology

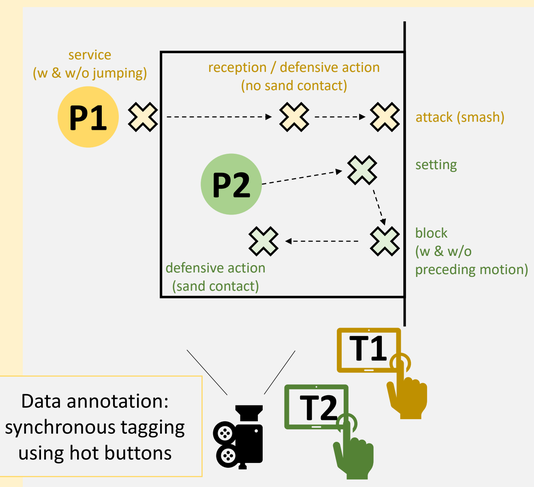
- Inertial measurement unit (IMU) from Movesense: 36.6 x 36.6 x 10.6 mm, 10 gr., chipset: Nordic Semiconductor nRF52832) with 64 kB RAM and 512 kB FLASH memory
- 3D accelerometer (ACC, ± 16 g) and a 3D gyroscope (GYRO, ± 2000 dps)
- Recording frequency of the IMU data (ACC and GYRO): 104 Hz
- Recording software: Data Collector 2.0 (Kaasa solution GmbH)



Data collection

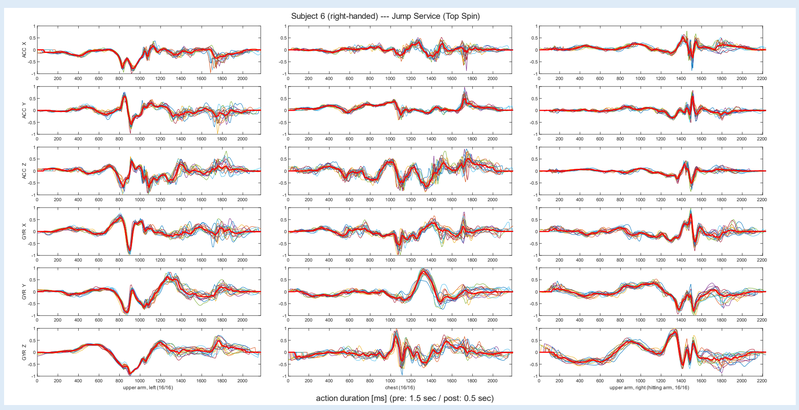
Actions performed for two different positions

Position 1	Position 2
• Service (with/without jumping) • Pass (standing) • Attack (smash)	• Set • Block (isolated/with preceding motion) • Defense / dig with sand contact



Data organization, preparation and analysis

Organizing and visualizing



Event detection

- Two-stage sliding window approach (0.5 sec)
- Stage I: suprathreshold L2-normalized values of accelerations and angular velocities of the sensor on the hitting arm (right arm).
- Stage II: suprathreshold upward rotations of the hitting arm and supporting arm

Action classification

- 1.5 seconds before to 0.5 seconds after the annotated ball hit point / event detection

(a) normalized feature vector classification

- Naive Bayes, kNN and C4.5 Decision Tree with statistical (min, max, mean, etc.) and specific features (e.g., rotation during the event)
- Cross-Validation (CV) and Leave-One-Subject-Out Cross-Validation (LOSO-CV) [Embedded Classification Software Toolbox (Ring et al., 2012)]

(b) sequential neural network model [tensor flow light]

- 70% training, 15% test, 15% validation

Model validation and system implementation

Event detection

- 1481 events detected (1040 true positive / 441 false positive)
- 1346 manually annotated actions
- Recall: 77.3% (306 false negatives) / Precision: 70.2%

Classification accuracy	Naive Bayes	kNN (k=3)	C4.5
CV	91.7%	94.7%	85.6%
LOSO-CV	82.0%	79.2%	75.4%
sequential neural network model : 90.1%			

Action classification

	Annotated action	Service (no jump)	Jump service (top spin)	Set	Attack (Smash)	Block (isolated)	Block (with pre-movement)	Defense / pass	Intensive defense (sand contact)	Total number
	Quantity	117	87	228	221	136	97	216	198	**1300**
	Percentage	9.0%	6.7%	17.5%	17.0%	10.5%	7.5%	16.6%	15.2%	Accuracy
classified as...	Service (no jump)	117	1	0	0	0	0	0	0	99.2%
	Jump service (top spin)	0	82	0	6	0	0	0	1	92.1%
	Set	0	0	211	0	5	2	0	2	95.9%
	Attack (Smash)	0	4	0	214	1	3	0	2	95.5%
	Block (isolated)	0	0	2	0	98	15	1	0	84.5%
	Block (with pre-movement)	0	0	7	1	27	73	2	8	61.9%
	Defense / pass	0	0	7	0	4	2	213	1	93.8%
	Intensive defense (sand contact)	0	0	1	0	1	2	0	184	97.9%
	correctly classified				**1192**					**91.7%**
	misclassified				**108**					**8.3%**

Confusion Matrix with Naive Bayes Classification and Cross Validation (CV)

Bibliography

Ring, M., Jensen, U., Kugler, P. & Eskofier, B. (2012). Software-based Performance and Complexity Analysis for the Design of Embedded Classification Systems. In IEEE, *Proceedings of the 2012 21st International Conference on Pattern Recognition (ICPR)*.

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