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OPEN Identifying neuromuscular and mental fatigue in elite youth table tennis players using machine learning

Thibault Delumeau^{1✉}, Thibault Deschamps², Christophe Plot¹, Eric Le Carpentier³ & Pierre Mousseau¹

Performance in table tennis is known to be affected by both mental and physical fatigue. However, accurately predicting a player's fatigue state remains challenging, particularly when using non-intrusive measurement protocols. This study proposes a methodology for detecting fatigue based on the analysis of players' movement patterns following controlled fatigue induction in young elite table tennis players. Player movements were recorded using an instrumented racket equipped with an accelerometer and pressure sensors. Mental and physical fatigue were induced using established protocols and were validated through significant changes in reference markers, including the Rating of Perceived Exertion for mental fatigue ($p < 0.05$) and Maximum Voluntary Contraction for physical fatigue ($p < 0.05$). The resulting labelled datasets were used to train supervised machine learning models for both binary fatigue detection and multiclass fatigue classification. Among the evaluated models, K-Nearest Neighbors and Random Forest achieved the best performance, with recognition rates of approximately 84% for binary classification and 82% for multiclass classification. These results demonstrate that combining formal fatigue induction with instrumented movement analysis enables the creation of reliable datasets for predicting players' fatigue states from their gestures.

Keywords Table tennis, Fatigue, Machine learning, Racket, Sensors

The fatigue, in its broadest sense, including both its mental and neuromuscular dimensions, has been extensively explored in various contexts such as industrial^{1,2}, military³⁻⁷, and in everyday activities (e.g., progressive loss of sustained attention across time-on-tasks; driving⁸ or performing a 12-h surgery after a typical clinical workday⁹). In the sports performance, by distinguishing the physical fatigue as an "alteration of performance induced by physical exercise"¹⁰ from mental fatigue defined as "a psychobiological state caused by a long period of cognitive activity and characterized by feelings of exhaustion and lack of energy"^{11,12}, many studies and systematic reviews have highlighted the distinct and specific effects of mental and/or physical fatigue on motor/sport performance¹³⁻¹⁸. For example, sport performance impairment is associated with an increased subjective feeling of tiredness, a lack of energy, and a perceived increase in effort. Furthermore, if mental fatigue affects endurance and motor skills, it does not impact maximal force production capacity¹⁶. This extensive research work provides a solid foundation for understanding the impact of mental and physical fatigue on sport performance.

Within this specific sport framework, some studies have specifically addressed the effects of fatigue on motor skills and behavioral performance, in racket sports^{19,20}, such as tennis^{21,22}, badminton²³⁻²⁶, and table tennis²⁷⁻²⁹. Significant examples include the works of Le Mansec et al.²⁷⁻²⁹, who reported that mental fatigue does impair table tennis performance in experienced adult players, evidenced by a decreased ball speed (-2.2%), accuracy (-3.9%), and an increasing number of faults ($+5.4\%$) during a table tennis performance test. The effects of an experimentally induced biceps fatigue on table tennis performance also induced an increasing number of faults ($+7.4\%$), and a decrease in accuracy (-6.7%), but this decrease in accuracy was specifically associated with an increased ball speed ($+3.4\%$). While a (simulated) table tennis competition induces significant muscle fatigue²⁷, Habay et al.³⁰ confirmed that mental fatigue negatively impacts table tennis performance in experienced players, specifically reaction time on visuomotor tasks. To that extent, even if no measure of racket's acceleration has been recorded in those works, specific adaptation of motor kinematic behavior (e.g., movements or racket's

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acceleration) can be suggested in the presence of neuromuscular or mental fatigue. For instance, Missenard et al.³¹ found changes in velocity and (peak) acceleration profiles during a pointing movement task (using the Fitts's law to trade between speed and accuracy in goal-directed movements) as a function of experimental conditions (pre vs. post muscle fatigue). Precisely, they showed that peak acceleration decreased with the task's difficulty and with muscle fatigue. In the same vein, some studies showed significant and distinct differences in accuracy and kinematics of dart throwing as a function of experimental mental vs. muscular fatigue conditions (Meymandi et al.³²).

While the effects of fatigue on sports performance are now well established, particularly in table tennis²², the (early) detection of players' state of fatigue throughout a match or even a longer period of time (i.e., training periods) is a major and exciting challenge for the scientific, medical, and high-level sports communities. In the industrial sector, the non-invasive objective detection of operators' (mental) fatigue is crucial for reducing accident risk and ensuring operator health³³. In the same vein, the current trend is to detect and predict fatigue in "real time" with machine learning approaches by using wearable devices/sensors^{34–40} for developing digital (bio)markers of fatigue in patients⁴¹ and athletes⁴². Interestingly, the use of machine learning models⁴³ for such purposes leads to very promising results by identifying precisely an individual's gait signature^{44–47} based on pattern recognition⁴⁸. For example, during walking at self-selected³⁸ and a large range of walking speeds⁴⁷, individuals were successfully identified by a machine learning algorithm from their muscle activation patterns (containing electromyographic signals), suggesting that the control of locomotion is unique to each individual.

The algorithms of supervised learning are now well established, and numerous benchmark studies are used to compare the accuracy of models based on different types of data (nominal, ordinal, discrete, or continuous). Most of the input data for these models comes from wearable Inertial Measurement Unit (IMU) measurements, providing real-time feedback signals through accelerometers and/or gyroscopes^{49,50}. In this respect, supervised learning problems are divided into two distinct categories, depending on their specific purpose: classification and regression. In the case of gesture recognition, it presents a classification challenge. For detecting human states of fatigue, it could be both, but it is still mainly a classification issue.

To address the issue of detecting mental and physical fatigue in nine young elite table tennis players while performing a specific table tennis test protocol⁵¹, we used a racket instrumented with an IMU and pressure sensors developed for measuring individual player stroke signatures from directly collected acceleration signals. By replicating the same protocol of Le Mansec et al.²⁸ to induce experimentally mental and physical fatigue, as compared to a control condition (watching a movie), we hypothesize that changes in the specific stroke related acceleration profile of the racket are distinctly consistent across the three fatigue conditions, meaning that particular fatigue state could be detected using the acceleration patterns measured in real-time. We expect that these findings will guide researchers, coaches, and players on how to best cope with the specific effects of fatigue on their behavioral performance (ball speed and accuracy, and decision-making) during training and games.

Methods

Participants

Nine of the best young male players from the French Elite table tennis centre volunteered to participate in the study (mean age: 15 ± 1.5 years; 5 right-handed players; national French table tennis ranking: 2104 ± 344 points). Inclusion criteria to take part in this study were to be part of a high-level structure, have no medical contraindications, and be available for at least one and a half months to complete the 3 different fatigue sessions (at least three-days recovery in-between): the mental condition (fatigue induced by mental exertion), the physical condition (fatigue induced by physical exertion involving the elbow flexors), and the control condition. It should be noted that, by definition, there are few expert players, which explains the very low sample size and the crossover design presented below.

This work was conducted in accordance with the Declaration of Helsinki and its latest amendments. The local ethics committee for non-interventional research at Nantes University (n° IRB: IORG0011023) has approved the following procedures (approval number: 02062023). Each player was informed about the nature of the study's protocol and provided written informed consent, as did their legal representative when they were minors.

Materials and apparatus

Individual profile of gesture

The player's movement profile was recorded using a dedicated racket instrumentation. A 3D accelerometer (ADXL326 ± 16 g, from Analog Devices) was placed in the handle of the racket to observe the player's acceleration profile while hitting the ball (Fig. 1A). The sensor's sensitivity is given by the datasheet and is 57 ± 6 mV/g for each axis. The sensor bandwidth ranges from 550 Hz to 1.6 kHz. The maximum acceleration value was stored as an acceleration indicator (in g). Four force-sensing resistors (FSR) were placed in the racket (Fig. 1B,C): two in the handle (red side and black side), and two for sensing the thumb-index pressure on both sides of the blade. Pressure profiles were measured in volts (V) after passing through an electronic conditioning circuit. Data is transmitted from the racket to the acquisition unit via ribbon cables approximately 3 m in length. The characteristics of such a transmission line are as follows: $0.148 \Omega/\text{m}$ and $1.45 \mu\text{H}/\text{m}$. An intermediate electronic module placed between the sensor and the acquisition unit allows signals to be preconditioned and ensures their integrity (buffer function).

Acceleration and pressure profiles were recorded at 50 kHz (or a Sampling period of 20 μs) using a high-resolution oscilloscope (12-bit resolution), Picoscope® 4000A Series from Pico Technology. Signals were low-pass filtered at 25 Hz to eliminate acquisition noise on accelerometers. Signals from a typical topspin forehand are given in Fig. 2. The acceleration profile used is the standard for the three components of the accelerometer, calculated by the following equation: $\sqrt{A_X^2 + A_Y^2 + A_Z^2}$ With A_X , A_Y , A_Z the acceleration on X,Y,Z axis

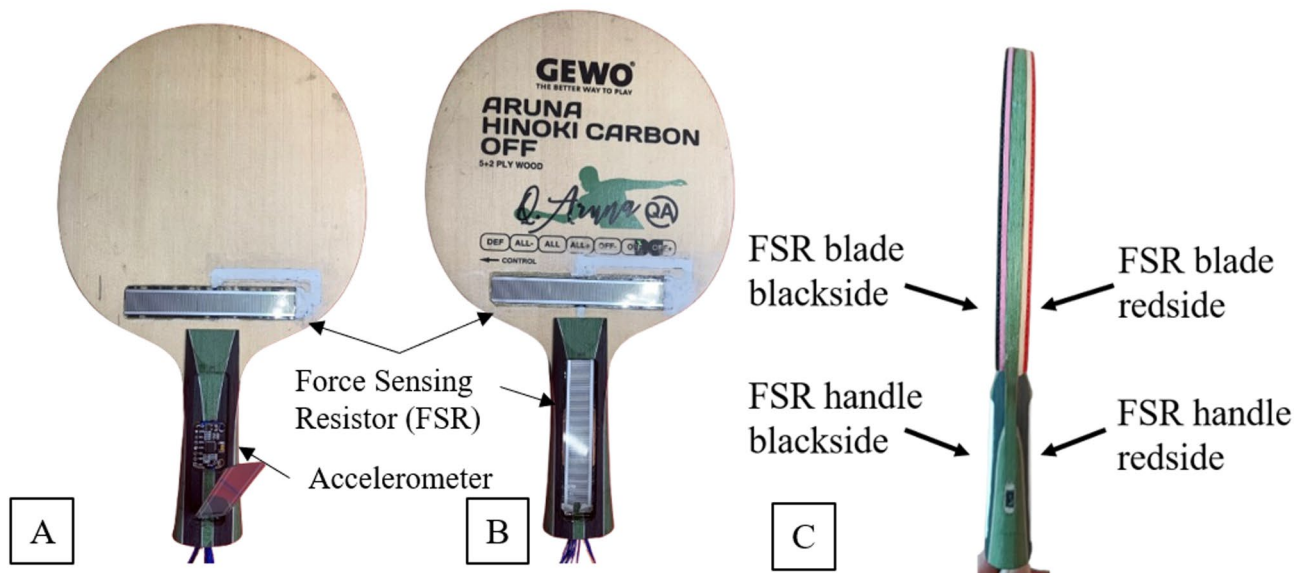


Fig. 1. Instrumented table tennis racket. (A) 3D Analog accelerometer is placed into the handle. (B) FSR is placed in the handle, and the blade (symmetrical). (C) FSR placement (side view).

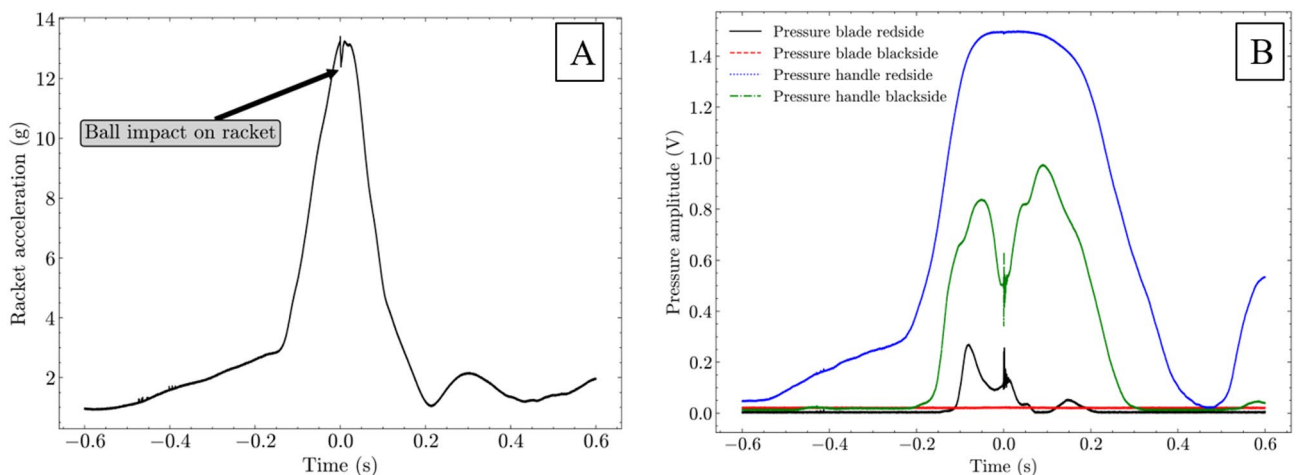


Fig. 2. Synchronized racket measurement signals from a forehand stroke. (A) Acceleration profile of the racket. (B) Multiple pressure profiles applied to the racket.

respectively. The pressure signals are left raw. The measured data (acceleration and pressure profiles *4) were normalized to the maximum value of the data series and then concatenated into a single data vector as a single input. The ball impact on the racket was recorded on the accelerometer (Fig. 2A) and FSRs (Fig. 2B); Note that the figures were centered at time equal to 0 corresponding to the ball-racket contact.

Experimental protocol

The current crossover design was primarily based on the protocol of Le Mansec et al.²⁸, with the expectation of replicating the same behavioral performance results (i.e., a decrease in ball speed and accuracy after the induction of both mental and physical fatigue) in young elite table tennis players.

Three experimental sessions were performed to determine the effects of different fatigue conditions on table tennis performance: a control condition, a mental fatigue condition, and a physical muscle fatigue condition targeting the biceps brachii. A typical session consisted of pre-fatigue tests and assessments, an experimental induction of the fatigue condition, and then post-fatigue tests identical to the pre-tests, as presented as follows.

Pre and post-tests and assessments

Psychological measurements

The fatigue was first assessed through the players' subjective feelings of fatigue by using a Visual Analog Scale (VAS). Players were asked to draw a mark on a 10 cm straight line reflecting their current state of fatigue (with 0 = no fatigue at all; 10 cm = extremely fatigued). The measured distance was converted into a VAS score out of 10. No dissociation was made between mental and physical fatigue; players were asked to report their general feelings of tiredness and lack of energy at the time they completed the VAS. By assessing feelings of fatigue *before and after fatigue conditions*, we aimed to determine the successful experimental induction of fatigue manipulation. Likewise, the perception of effort was measured using the ratings of perceived exertion (RPE) scale^{52,53} to quantify the feeling of exhaustion of the player. Lastly, a workload assessment was carried out using the National Aeronautics and Space Administration Task Load Index (NASA-TLX)⁵⁴ test to identify its nature by breaking down the task workload into 6 subscale categories: (i) mental demand, (ii) physical demand, (iii) temporal demand, (iv) performance, (v) effort, and (vi) frustration.

Table tennis performance test

Before and after the induced fatigue condition, the player carried out a specific table tennis performance test, consisting of 4 different stroke conditions (30 balls each): forehand on backspin ball (Stroke 1), backhand on backspin ball (Stroke 2), forehand topspin on topspin ball (Stroke 3), and backhand topspin on topspin ball (Stroke 4). Following a warm-up for about 5–10 min, this table tennis performance test lasted approximately 5 min for all stroke conditions. The player was instructed to hit the ball as they would in a match while targeting a defined accuracy zone marked out on the table by a target of the size of the ball. The targets were placed approximately 10 cm from the side and 20 cm from the back of the court. The balls were thrown by an Amicus Expert ball-throwing robot from Butterfly, always launching balls with the same characteristics for each single stroke condition: frequency, placement, speed, and spin. After completing this performance test, the player was asked to rate the effort related to this table tennis task by using the RPE scale.

Maximal voluntary contractions (MVC) of the biceps brachii

Before and after the tested fatigue condition, the torque production capacity of the elbow flexor (biceps brachii) of the player was measured on the preferred hand. After a 5-min warm-up period consisting of various submaximal contractions (approximately 8 s) ranging from 20 to 80% of the estimated MVC, each player had to perform two 5-s MVC tests, with 1 min of recovery time between the two tests (see Fig. 3B). The highest MVC achieved was used as the maximum force reference for the player. This protocol was repeated after fatigue induction as a post-assessment of MVC. All the MVC of the elbow flexors were performed with an elbow joint angle at 90° (0° = arm fully flexed) and the shoulder at 90° (0° = full shoulder abduction), and measured using a homemade ergometer (Fig. 3A). A typical MVC assessment is visible in Fig. 3B.

The ergometer is an MTS Systems S-type load cell with a measuring range of 0 to 100 daN. The sensor, which is a strain gauge (force cell), is connected to a Wheatstone bridge-type conditioner and has been calibrated beforehand. The signals were recorded by the digital oscilloscope with a sampling frequency of 10 kHz.

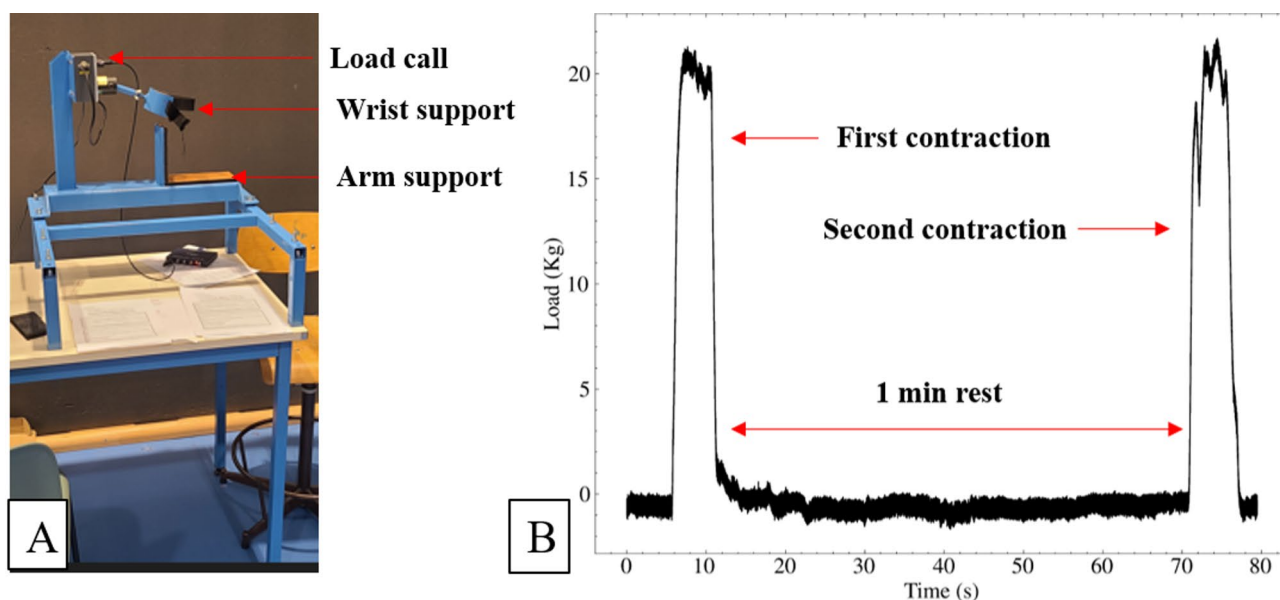


Fig. 3. Measurement of maximum voluntary contraction (MVC). (A) Experimental ergometer used to measure MVC. (B) Typical load profile during an MVC assessment with 2 contractions.

Fatigue conditions

Mental fatigue

The mental fatigue session consisted of performing the AX-Continuous Performance Test⁵⁵ (AX-CPT) for a duration of 90 min. Briefly, the AX-CPT is a version of the continuous performance test in which the player, seated in front of a computer screen, is asked to press a specific key as quickly as possible without making a mistake when the letter X (target signal) is presented after the letter “A” (valid signal) and not to respond to all other stimuli. Each stimulus was presented for 300 ms in the middle of the screen. The inter-stimulus interval was set at 1200 ms. The “A–X” sequence has a frequency of appearance of 70% and the other sequences of 10% (“BX” sequence, in which an invalid signal (i.e. non- “A”) precedes the target signal (“X”); “AY” sequence, in which the valid signal is followed by a non-target signal (non- “X”); “BY” sequence, in which the valid signal and target signal are incorrect. This test is well known to induce mental fatigue⁵⁶ and is used broadly in the literature.

Physical (biceps brachii) fatigue

During the physical muscle condition, the player had to perform several repetitions of maximum eccentric contractions of the biceps brachii of the effector arm (contractions separated by 30 s of recovery, performed at a speed of 60 degrees per second), in such a way as to induce a 15% reduction of their MVC²⁸. This target was chosen based on a previous study that showed a 15% decrease in torque production capacity of the knee extensors following a table tennis competition⁵⁷. To this end, an initial series of ten repetitions was performed, followed by an evaluation of the MVC to assess its impact on the percentage reduction of MVC. If the 15% was not achieved, a following series of 5 contractions was performed until the 15% target was reached. To this end, a workload determination session was carried out before the fatigue sessions. Determination of the maximum repetition load for one repetition (1-RM) was carried out in the same environment as the training venue, by using the following protocol. Using a Larry Scott-type bench, the player was asked to perform a biceps-curl movement with the effector arm under load. He had to perform a series of 10 loaded repetitions, followed by a 2-min rest period, before slightly increasing the load until exhaustion. To protect the physical integrity of the young athletes, who were neither physically developed (growth peak not reached) nor familiar with isolated muscular exercise on the biceps, the loaded test was stopped when the player showed visible difficulty. An extrapolation of the 1-RM was carried out using the formulas from Wood et al.'s work⁵⁸. A custom induction bench has been used to perform the eccentric contractions; a simplified description of the movement is given in Fig. 4A. A typical MVC profile pre-post physical (biceps) fatigue induction is given in Fig. 4B.

Control condition

During the control session, the player watched a 90-min film to watch (the same duration as the mental fatigue task) while sitting comfortably. The chosen film, “Home” by Y. Arthus-Bertrand, is recognized as cognitively neutral regarding fatigue. This control condition is classically used in the scientific literature to examine the effects of mental fatigue on performance^{28,56,59,60}. In summary, each player took part in three experimental sessions (+ a workload determination session for the physical fatigue), with an overview of a fatigue session in Fig. 5.

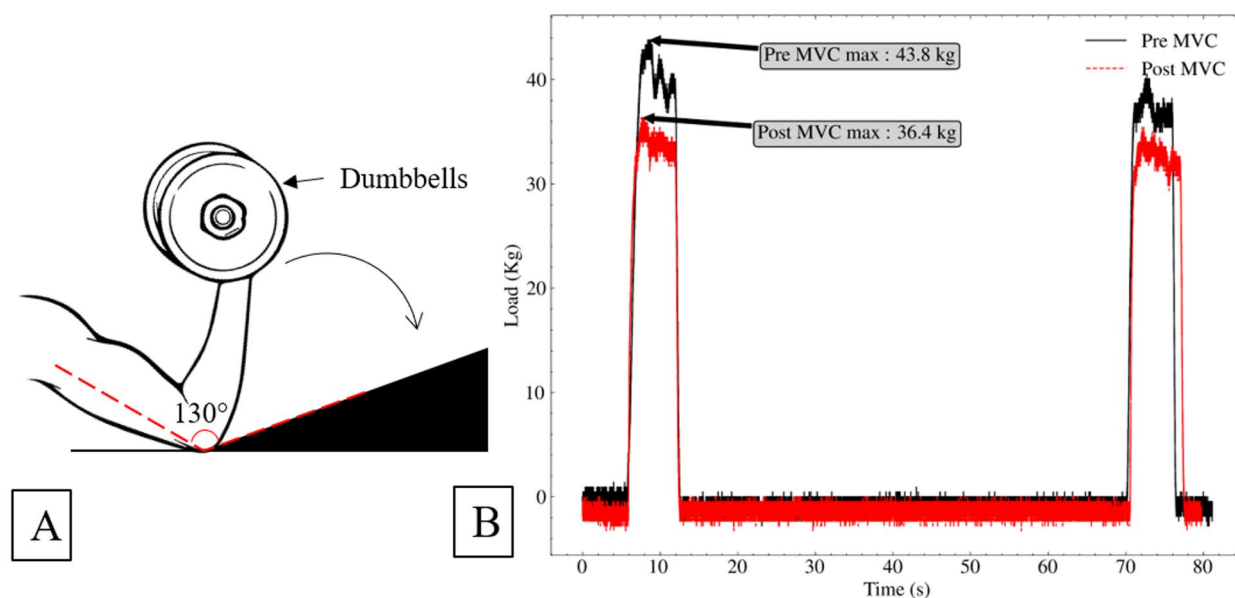


Fig. 4. Physical fatigue induction in the biceps brachii. (A) Induction bench used to perform the maximal eccentric contractions. (B) MVC profile pre-post physical fatigue induction showing a loss of ~ 15% force production capacity.

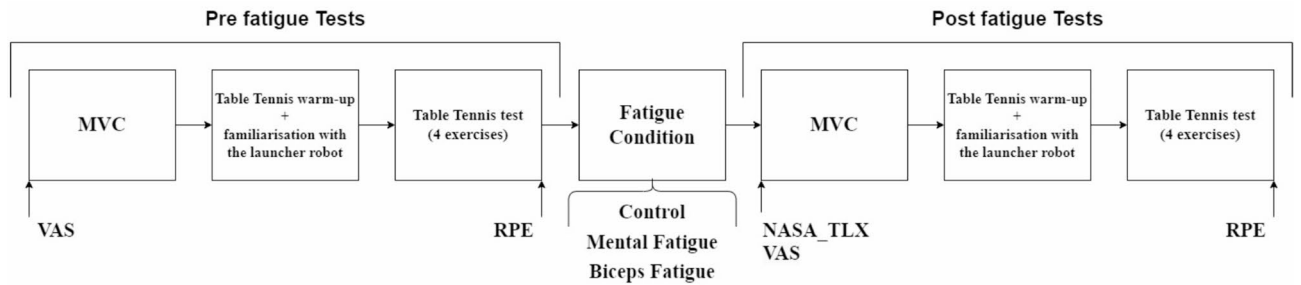


Fig. 5. Overview of the proposed fatigue induction protocol.

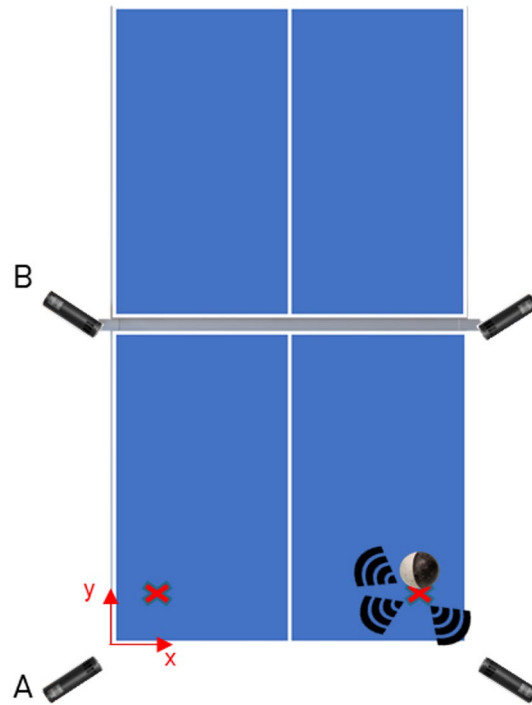


Fig. 6. Microphone positioning for measuring accuracy using an acoustic method based on a TDOA model.

Data collection

Table tennis performance measurements

For each player, the linear speed (m s^{-1}) was measured at the net using optical sensors during the table tennis performance test. The measurement is performed by an IR-LED barrier, which calculates the flight time between two points separated by a known distance, then computes ball speed. This device is the result of previous research into measuring ball rotation, where the operating principle is described in more detail⁵¹. The measurement error of this device, which measures speed in 1-D, is 1.5% per 10° of the incoming ball's trajectory. Due to the speed reduction caused by air friction, we decided to position this one-shot measurement as close as possible to the point of impact of the ball on the table. This choice is more representative of the speed of the ball received by the receiving player in a real situation. Furthermore, positioning it in a single location makes all of the measurements consistent and comparable. The player's accuracy was also measured by calculating the distance from the point of ball impact to the target (in cm) and by the percentage of successful balls in a series of 30 balls. Accuracy was measured by estimating the distance (in cm) between the impact position and the position of the associated target (right or left, depending on the strike). This estimate is made using a TDOA (Time Difference Of Arrival) model based on acoustic signals (sound of impact). Four cardioid microphones (CM4 from Audioware) were positioned around the table, and signals were acquired using the same parameters as described above. An explanatory diagram of the acoustic measurement for accuracy is shown in Fig. 6.

A, B, C, D being respectively the sensors' position $[x, y]$. The red crosses indicate the position of the left and right targets. The accuracy of this technique is estimated at ± 2 cm in real conditions. Using the instrumented racket introduced previously, the normalized acceleration profile and the pressure were recorded for each stroke. The acceleration profile used is the standardized acceleration signal calculated using the three components. The

Fatigue state	Training set	Test set	Total
Control	894	211	1105
Mental Fatigue	959	242	1201
Physical (biceps) Fatigue	749	198	947
Total	2602	651	3253

Table 1. Overview of the dataset and breakdown of the training and test sets.

Model	Hyperparameter	Range
KNN	N-Neighbors Distance	[2–7] [Manhattan/Euclidean]
Decision Tree	Depth Decision criteria	[2–10] Gini/Entropy
Random Forest	N-estimators Depth Decision criteria	[100,200,500] [2–10] Gini/Entropy
SVM-RBF	C Gamma	[0.1,1,10,100] [1,0.1,0.01,0.001]
SVM-Linear	C	[0.1,1,10,100,1000]

Table 2. Overview of hyperparameters to be optimized.

pressure signals are left raw. The measured data (acceleration and pressure profiles *4) were normalized to the maximum value of the data series and then concatenated into a single data vector as a single input.

To examine the effects of fatigue conditions on table tennis performance, we used the average of each physical and behavioral parameter measured (acceleration, pressure, and accuracy) on the 30 balls of a player's series. Thus, the performance indicators presented here are defined by Eq. (1).

$$\overline{\varepsilon}_{f,t,e,j} = \frac{1}{N_p} \sum_{i=1}^{N_p} \varepsilon_{i,f,t,e,j} \quad (1)$$

ε The performance indicator to be processed, f The fatigue condition [Mental Fatigue (MF); Physical Fatigue (PF); Control (C)]. t The temporality of passage [Pre; Post], e Current stroke condition [1;2 ;3;4]. j The player [1; ...; 9]. N Number of balls of the series ($N = 30$). N_p The number of valid balls of the series with $N_p \leq N$. i Index of the ball to consider.

Datasets and machine learning models

To detect the fatigue state of a player, given the typical pressure and accelerometric signals during a stroke, data labeling was crucial. Thus, each ball hit has been labeled according to the fatigue condition, the temporality of the test (pre vs. post). Outliers, such as missed balls (where the racket didn't hit the ball), were eliminated, resulting in a total of around 6480 ball hits being recorded.

To ensure the reliability and consistency of the model, according to the well-known saying of programmers, “garbage-in, garbage-out”, only post-fatigue labeled data were kept to feed the machine learning models, so only 3253 data points were used. Data was split into a train-test dataset (80% for training and 20% for testing) to keep a reasonable number of samples for representative testing. The dataset is described in Table 1.

According to the scientific literature, only the most-used models were currently tested, including the Support Vector Machine (SVM) with different kernels (linear and radial), k-nearest Neighbors (KNN), decision tree (DT), and random forests (RF). The models were created using Python V3.8.13 with the scikit-learn V1.8.0 library. A grid search hyperparameter optimization was realized on each model, and each best model went through a K-fold cross-validation process with $k=5$ folds. The values and ranges of the hyperparameters tested are given in Table 2. They were deliberately chosen to be low to minimize computation time and avoid excessive use of hardware resources.

Observed metrics for model performance were the most common ones: accuracy, precision, recall, F1-Score, Receiver-operating characteristic curve (ROC), and Area under the curve (AUC). The models' ranking was based on accuracy, and model evaluation of each class was realized using a One-Versus-the-Rest (OVR) strategy. We opted for a One versus the rest approach, which considers a multi-class problem in a binary manner. The tested class is considered positive, while the remaining classes are considered negative. This allows us to obtain a ROC curve for each class in our problem. Multiclass models were evaluated using macro-averaged metrics, which correspond to the arithmetic mean of all per-class metrics. We also performed a LOSO cross-validation test to observe the generalization of the proposed models.

Data and statistical analysis

Data distributions consistently passed the Shapiro–Wilk normality test, and thus, values are reported as mean \pm standard deviation. The effect of the fatigue conditions on VAS, RPE, and MVC was determined using

a 2-way analysis of variance (ANOVA) with repeated measures, that is, three (Condition—mental fatigue, physical fatigue, and control condition) \times 2 (Time—pre vs. post assessment). Similar ANOVAs were performed considering the table tennis behavioral performance, namely ball speed, accuracy, and faults. The level of significance was set at $p=0.05$. For all analyses, effect sizes were quantified as eta square (η^2), with medium and large effects considered for $\eta^2=0.06$ and $\eta^2=0.14$, respectively⁶¹. Bonferroni post hoc tests were performed following significant main effects (adjusted p values are reported). For NASA-TLX subscales, a Friedman test was conducted, and Conover post hoc tests were performed following significant main effects (adjusted p -values are reported). All statistical analyses were conducted using open-source JASP software (version 0.18.3.0). Accessed on 1 April 2024 at <https://jasp-stats.org/>.⁶²

Results

Statistical analysis

Markers of fatigue

First, there was no effect of fatigue condition, whatever the marker of fatigue (VAS, RPE, MVC) ($p>0.05$). However, there were significant differences as a function of time factor for the VAS score ($p<0.001$, $\eta^2=0.232$; pre vs. post= 2.5 ± 2 vs. 4 ± 1.7), RPE ($p<0.01$, $\eta^2=0.357$; pre vs. post= 2.5 ± 1.1 vs. 3.6 ± 1.5), and MVC ($p<0.01$, $\eta^2=0.251$; pre vs. post= 28.4 ± 7.1 kg vs. 26.1 ± 6.5). Note also that a significant Condition \times Time interaction was found for the three markers of fatigue: VAS ($p<0.05$, $\eta^2=0.146$), RPE ($p<0.05$, $\eta^2=0.092$), and MVC ($p<0.05$, $\eta^2=0.167$). The post-hoc tests found a significant difference between the pre vs. post MVC (29.1 ± 6.7 kg vs. 24.3 ± 5.3 kg; -16%) only in the physical fatigue condition ($p_{\text{Bonferroni}}<0.01$). A significant pre vs. post difference was observed on the RPE score in the mental fatigue condition ($p_{\text{Bonferroni}}<0.005$; pre RPE: 2.6 ± 1 vs. post RPE 4 ± 1.4 ; $+53\%$) and in the physical fatigue condition ($p_{\text{Bonferroni}}<0.001$; pre RPE: 2.3 ± 1.1 vs. post RPE 4 ± 1.2 ; $+73\%$). Lastly, the subjective feeling of fatigue via the VAS score, also showed significant pre vs. post variations ($p_{\text{Bonferroni}}<0.001$), only in mental fatigue condition (pre VAS: 2 ± 1.2 vs. post VAS 5.2 ± 1.7 ; $+160\%$) and physical fatigue ($+36\%$), compared with only 13% in the control condition. These results are visible in Fig. 7A–C.

To provide additional insight into the effect of fatigue conditions on the player's stage of fatigue for further statistical analysis, Friedman tests were performed on the values of the NASA-TLX questionnaire subscales. A function of fatigue conditions, there was a significant difference in effort ($p<0.05$), mental demand ($p<0.05$), physical demand ($p<0.05$), and frustration ($p<0.05$). Post-hoc tests showed significant differences for the effort subscale ($p<0.01$) between the control and the two mental and physical fatigue conditions, for mental demand between mental fatigue and the two other conditions, and for physical demand between physical fatigue and the two other conditions. No workload difference between the fatigue conditions was found on the temporal demand and performance subscales (Fig. 8).

Effects of the fatigue conditions on table tennis performance

No significant difference was observed between the fatigue conditions for table tennis performance indicators such as accuracy ($p=0.3$, $\eta^2=0.03$) and faults ($p=0.8$, $\eta^2=0.003$). Ball speed showed a significant difference ($p=0.029$, $\eta^2=0.111$). However, subsequent post hoc tests did not yield significant differences between individual conditions (all $p>0.05$). The pre-post variation we obtained for these indicators is shown in Table 3.

Fatigue detection using machine learning approaches

Binary approach

The first approach was to detect if fatigue could be easily detected as a whole. In other words, can a model detect the presence of fatigue or not? We used an alternative dataset where mental fatigue and physical (biceps) fatigue are defined as one unique class (fatigue class), and the control class was the no-fatigue class. The input data used for the models were the normalized acceleration profile and the four pressure profiles. The dataset used for binary classification is shown in Table 4.

After cross-validation and hyperparameter optimization, the test of the different models gives us the following results in Table 5.

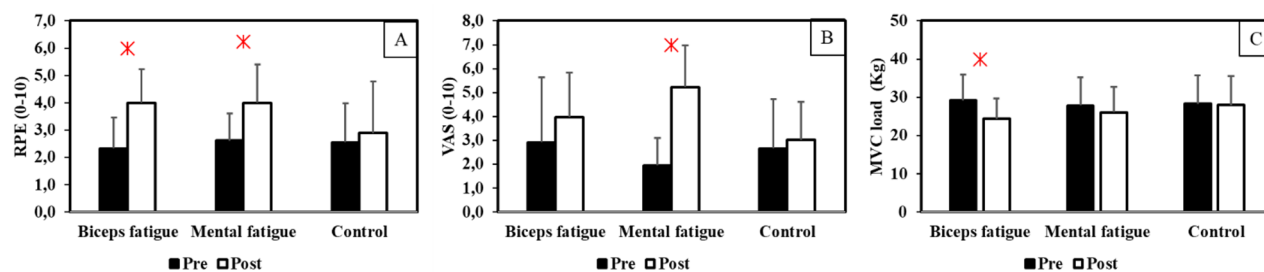


Fig. 7. Statistical analysis of markers of fatigue (* statistically significant with $p < 0.05$). (A) RPE (0–10). (B) Subjective Feeling of fatigue (0–10). (C) MVC load (kg).

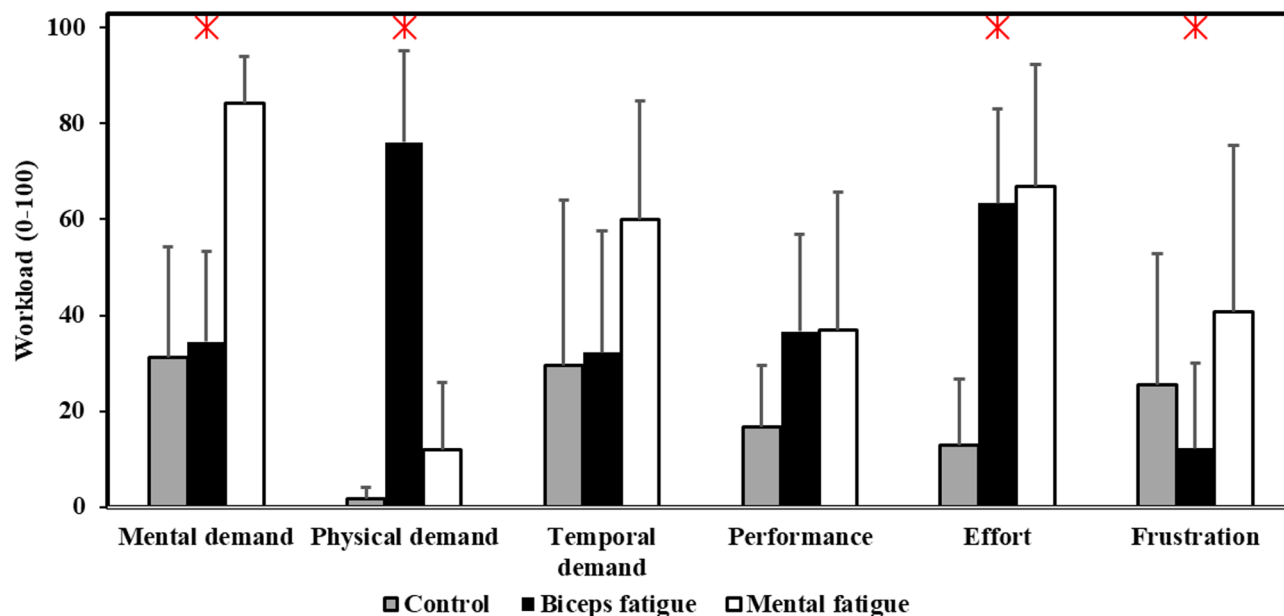


Fig. 8. NASA-TLX workload subscales. Data are presented as means ± SD.

Fatigue condition	Ball speed (%)	Precision (%)	Faults (%)
Control	- 0.1	- 1	+ 20
Mental fatigue	+ 1.2	+ 4.8	+ 23
Physical (Biceps) fatigue	+ 0.8	- 2.4	+ 13

Table 3. Performance indicator pre-post variation (%) on different fatigue conditions.

Fatigue state	Training set	Test set	Total
No fatigue	894	211	1105
Fatigue	1708	440	2148
Total	2602	651	3253

Table 4. Alternative dataset used for binary fatigue detection.

Rank	Classifier	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
1	KNN	84 ± 0.022	82 ± 0.022	81 ± 0.022	81 ± 0.022
2	Random Forest	81 ± 0.009	88 ± 0.009	72 ± 0.009	75 ± 0.009
3	SVM (linear)	77 ± 0.024	74 ± 0.024	72 ± 0.024	73 ± 0.024
4	SVM (RBF)	67 ± 0.004	84 ± 0.004	52 ± 0.004	43 ± 0.004
5	Decision Tree	63 ± 0.025	58 ± 0.025	58 ± 0.025	58 ± 0.025

Table 5. Performance of supervised learning models for the binary fatigue detection approach.

The best model based on accuracy was the KNN (84%), which is also the model with the highest f1-score of 81%. F1-score is a relevant metric used to compare classes with an unbalanced number of samples (here, the “fatigue” class is twice as large as the “No fatigue” class).

Multi-class approach

We currently aim at detecting the exact player’s specific state of fatigue (mental, physical, or control conditions) based on the racket’s signals. The dataset used for this purpose is presented in Table 1. After training all the models and cross-validating them, we obtained all the model performances based on the most used metrics in Table 6.

Rank	Classifier	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
1	Random Forest	82 ± 0.015	82 ± 0.015	82 ± 0.015	82 ± 0.015
2	KNN	80 ± 0.025	80 ± 0.025	80 ± 0.025	80 ± 0.025
3	SVM (linear)	63 ± 0.02	62 ± 0.02	62 ± 0.02	62 ± 0.02
4	Decision Tree	53 ± 0.012	54 ± 0.012	53 ± 0.012	53 ± 0.012
5	SVM (RBF)	40 ± 0.007	80 ± 0.007	35 ± 0.007	21 ± 0.007

Table 6. Performance of supervised learning models for fatigue classification.

Real class	Control	180	10	21
	Mental fatigue	19	217	6
	Physical (Biceps) fatigue	36	31	131
		Control	Mental fatigue	Physical (Biceps) fatigue
		Predicted class		

Table 7. Confusion matrix from the best model on the test dataset (N = 651).

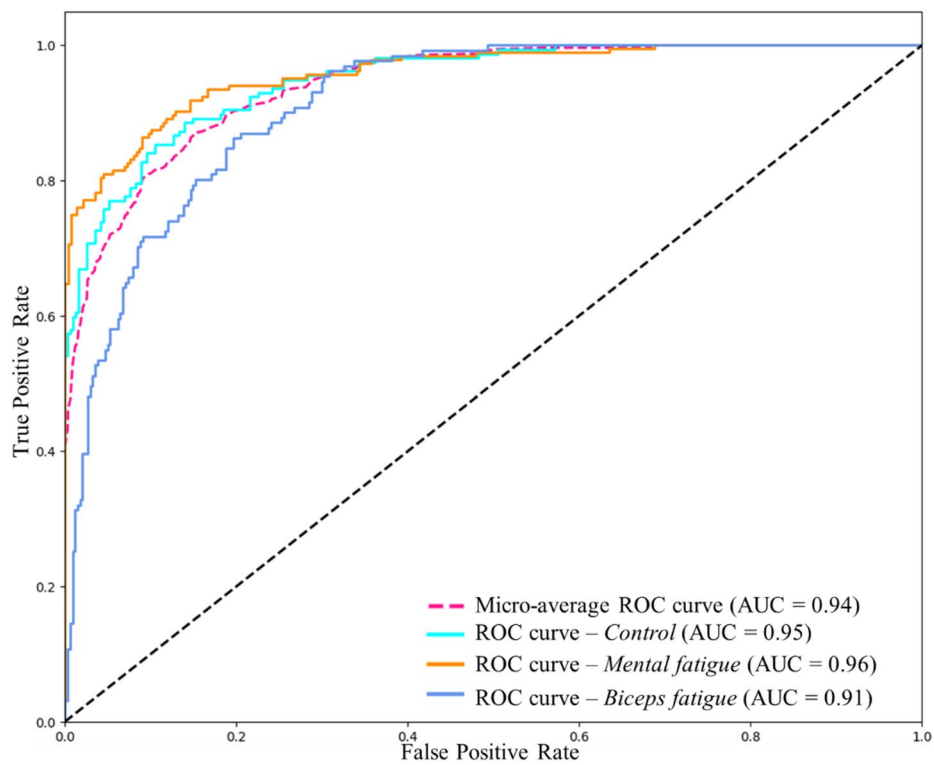


Fig. 9. ROC-AUC curve for the RF model on the fatigue classification task using racket data.

Hence, the Random Forest appears as the best model with 82% accuracy, just ahead of the KNN model with 80% accuracy. Overall, the other models show less accuracy on a multi-class approach than in a binary classification task. To get a bit more insight into the model prediction, the confusion matrix is given in Table 7

Lastly, the model performance is given by the ROC curves in Fig. 9.

LOSO cross validation

The results obtained by LOSO cross-validation are given in Table 8.

The model with the best accuracy after cross-validation is Random Forest, with approximately 40% fatigue recognition. For all models, it is interesting to note low variability despite the nine different folds (related to the nine players).

Model	KNN	RF	DT	SVM-RBF kernel	SVM-Linear kernel
Mean accuracy	34.20% ± 0.059	39.34% ± 0.135	34.72% ± 0.077	36.73% ± 0.056	35.33% ± 0.043
Mean Precision	35.60% ± 0.084	35.78% ± 0.16	37.11% ± 0.1	32.00% ± 0.165	37.11% ± 0.073
Mean Recall	33.42% ± 0.063	39.22% ± 0.136	34.78% ± 0.077	37.00% ± 0.057	35.44% ± 0.047
Mean F1-Score	32.20% ± 0.075	34.00% ± 0.14	34.11% ± 0.08	24.23% ± 0.085	33.47% ± 0.063

Table 8. Cross-validation results using Leave One Subject Out (LOSO).

Discussion

The present study aimed to determine whether accelerometric and pressure measurements obtained through an instrumented table tennis racket in elite young players performing a specific ball-hitting test under different fatigue conditions (mental, physical, and control) could serve as robust signals to detect the player's fatigue state. By using machine learning approaches, the main result was that the player's state of fatigue was consistently detectable with the highest inter-condition classification rates (>80%) for the random forest model, in both binary and multiclass approaches. Interestingly, these original inter-condition classification rate results appear to be currently more sensitive to accurately detecting the fatigue state than more traditional markers of fatigue at the behavioral level (e.g., a decreased ball speed and accuracy, and an increasing number of faults when mentally fatigued²⁶).

Fatigue induction validation

Physiological and psychological markers of fatigue

The effects of fatigue induction protocols strictly based on Le Mansec et al. study were firmly replicated in elite young players, as evidenced by changes in markers of fatigue. As necessary prerequisites, the experimental fatigue conditions induced before the specific table tennis tests are significantly associated with a decrease in MVC of elbow flexors (physical fatigue) and an increase in self-reported subjective fatigue (mental fatigue) and ratings in perceived exertion (mental and physical fatigue). These results are confirmed by increased NASA-TLX mental and physical workload scores after the mental and physical fatigue conditions, respectively. In accordance with our expectations, we were successful in manipulating different states of fatigue in table tennis players, which is consistent with previous studies^{56,59}.

Behavioral and performance markers of fatigue

Mental fatigue and neuromuscular fatigue are complex phenomena; coupling of effects is possible and may bias the results. It is known that a speed-accuracy trade-off can occur during mentally demanding tasks⁶⁰, but it is hard to measure if players were affected or not. Our test conditions are backed by significant statistical tests, and we believe these phenomena did not occur within our study's scope. Statistical analysis of typical performance indicators of table tennis has shown results that differ from Le Mansec et al. study²⁸, but this could be due to the nature of the test population, which is younger and probably more unstable.

Fatigue detection using machine learning

The first binary machine learning approach to fatigue detection showed very promising results, with the KNN model achieving the best accuracy with inter-fatigue conditions classification rates of 84% in or not. Besides a more advanced multi-class approach used for detecting the exact player's fatigue state, it also produced excellent results. The random forest model was the best with an 82% classification rate. For this model, the significant micro-averaged ROC-AUC shows a very high area equal to 0.94. There is a noticeable, slightly higher score for mental fatigue detection (AUC = 0.96) than for physical fatigue (AUC = 0.91). As far as we know, this is currently the first time that a specific fatigue state can be robustly detected in elite young table tennis players from the acceleration signals of their rackets.

Machine learning performance comparison

These promising results are consistent with numerous studies focusing on the human fatigue state detection issue (in other contexts) by using machine learning or deep learning models. For example, we can cite the work of Biró et al.⁶³, who realized a binary detection fatigue task based on an IMU dataset of running participants (n = 19). They obtained around 50% accuracy with a ROC AUC of 0.5 to 0.6 using DT or RF models. Fatigue was induced by a running test, but no assessment, such as RPE or subjective feeling of fatigue, was used to control a strict fatigue induction. Different models were tested, such as ensemble and tree-based models, more common ones (e.g., KNN, SVM with various kernels), and Long Short-Term Memory (LSTM), which performed better and showed a greater consistency, besides showing low accuracy.

More related works using IMU and/or ECG data combined with SVM-based models achieved higher accuracies, like the work of Guaitolini et al.⁶⁴ or Luo et al.⁶⁵, showing 84% and 93% accuracy on fatigue detection tasks. Fatigue was induced using a running test with a self-reported assessment of RPE, and fatigue prediction performed the best using an SVM with a Gaussian kernel. More complex models, such as LSTM and deep learning algorithms, have also been studied, with the work of Li et al.⁶⁶ and Guan et al.⁶⁷ achieving fatigue detection tasks with more than 90% and 60 to 80% accuracy, depending on the used model. These values are close to those obtained in this study, which confirms these results and the presence of fatigue in accelerometer-type signals obtained by IMUs.

However, it is difficult to compare the performance of the models presented in all the studies with ours due to the different protocols used. Our approach strictly validates fatigue induction through psychological tests, which is not present in all studies. In addition, fatigue induction remains relatively vague in most studies combining machine learning and fatigue (e.g., what type of fatigue is induced? Physical? Mental? Which muscle groups are targeted?) As for the models used, they are similar in most cases. However, performance seems to vary between studies, probably due to input data with more instabilities, or models that are not optimized and adjusted to the dataset.

Cross-validation LOSO

The results of LOSO cross-validation, which is the most rigorous method for testing model generalization, were significantly lower than those of K-fold cross-validation. This difference can be explained mainly by the small number of subjects ($n=9$), which has a significant impact on learning when reduced to $n=8$ subjects, especially since the latter have heterogeneous skill levels. This method will greatly penalize the model, particularly when the “weakest” players are in the learning game. The results speak for themselves, ranging from 34 to 40% recognition of fatigue. The generalization of such a model, therefore, seems unlikely to be promising based on such a small number of participants. However, in a high-performance use case, where cohorts of players are small and change little over time (once a player has entered a high-performance structure, they will remain there for several years or more), it seems reasonable to think that such models could be retrained regularly (every X months or years). This model retraining phase could allow for the inclusion of any new players and the removal of outgoing players. This would, of course, require repeating all the fitness tests for new players, but also those already passed in order to update the model according to the technical progress or physiological maturation of the young players.

Sensor development

The development of an instrumented racket and sensors placement played a crucial role in player gesture measurement and also in getting machine learning models demonstrating high accuracy. This sensor development is similar to Blank et al.'s^{68,69} work, which mainly focuses on embedding electronics into the racket rather than analyzing the gestures of players. The analysis of accelerations in table tennis has been largely studied^{68,70,71} but is missing a real breakdown of a player's movement to identify movement optimization. The same goes for the hand dynamics, where future studies should place more focus on the analysis of racket holding to understand its mechanisms. This combination of racket acceleration profile and holding mechanisms (pressure sensor waveforms) could be used for the identification of potential individual signatures for each player.

Limitations

This current study has shown promising results for fatigue detection in table tennis based on instrumented racket measurements. However, it came with limitations that should be acknowledged when interpreting the presented findings.

Sample size

Despite having a cohort of young experts, the small sample size ($n=9$) may reduce the statistical power of the analyses and limit the generalizability of the results. Moreover, the players were not fully representative of the elite population in terms of age or gender. Future research should include larger and more diverse participants to strengthen the results of this paper.

Measurement limitations

In this study, multiple assessment tools were used to report physiological or psychological behavior. Most of them are self-reported or subjective measures such as VAS, RPE, and NASA-TLX, which are subject to bias. The measurement of stroke profile combining multiple sensors in the racket (1 IMU + 4 pressure sensors) is an original contribution, as there is no other study to our knowledge that uses pressure sensors in a table tennis racket, but it comes with some limits as well. In order to preserve the integrity of the racket and not degrade the player's feel, the placement of the pressure sensors on the board (Pressure blade sensors backside and redside) is difficult to access for players with small hands. This may impact the pressure profiles measured on these two sensors, as some players did not have hands large enough for a measurement signal to be recorded. The impact of this lack of information is complex to assess because some players do not apply much or any pressure voluntarily, highlighting the possible presence of activation patterns specific to each player.

Machine learning models

The machine learning models used in the study are the most common ones, and even if they provide satisfying results to detect fatigue state in players, more specific models should be considered for testing. Although the results obtained are very good in the case of k-fold cross-validation, the more stringent LOSO cross-validation does not allow conclusions to be drawn about the generalization of such models, at least in a context that is more open than that of a cohort of professional players within the same training centre. As the input signals of the models are time series, exploring deep learning models should be interesting, as there are plenty of techniques for multiclass classification tasks⁷². Another practical limitation is the fatigue detection models' “offline”, which is satisfying for research purposes but could be limited for real case application where “in line” models could bring more value to the players, and their coaches in the context of table tennis fatigue detection.

Conclusion

In this research paper, we presented a complete methodology to produce fatigue data based on young high-level table tennis players' profiles during stroke conditions. The fatigue induction protocols were validated with statistically significant changes in objective and subjective markers of fatigue, evidencing the well-induced of both mental and physical fatigue. On a behavioral level, results showed consistency with the scientific literature, although they were no statistical validation. Data collection from an instrumented racket while performing a table tennis performance test gives information on the individual acceleration and pressure profiles during four different strokes. These data were used to train multiple supervised learning models to accurately predict the fatigue experienced by the player with high classification rates for KNN and Random Forest models, in both binary and multiclass approaches. However, these models were tested « offline », and future work should deploy them for “in line” fatigue detection classification tasks.

Data availability

The data presented in this study are available on request from the corresponding author. The data are not publicly available due to confidentiality concerns.

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Author contributions

Conceptualization, Thibault Delumeau, Thibault Deschamps, Christophe Plot and Pierre Mousseau; Data collection, Thibault Delumeau, Christophe Plot and Pierre Mousseau; Data analysis, Thibault Delumeau and Thibault Deschamps; Methodology, Thibault Delumeau, Christophe Plot, Eric Le Carpentier, Thibault Deschamps and Pierre Mousseau; Software, Thibault Delumeau; Supervision, Thibault Deschamps, Pierre Mousseau; Validation, Christophe Plot, Eric Le Carpentier, Thibault Deschamps and Pierre Mousseau; Writing—original draft, Thibault Delumeau; Writing—review & editing, Thibault Delumeau, Christophe Plot, Eric Le Carpentier, Thibault Deschamps and Pierre Mousseau. All authors have read and agreed to the published version of the manuscript.

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Competing interests

The authors declare no competing interests.

Informed consent

The authors confirm that all methods presented in this paper were conducted in accordance with the Declaration of Helsinki and its latest amendments. The local ethics committee for non-interventional research at *Nantes University* (n°IRB: IORG0011023) has approved the presented procedures. The authors confirm that informed consent was obtained from all subjects and/or their legal representative.

Consent for publication

The authors declare that informed consent was obtained from all subjects and/or their legal representative for the publication of personal information/images in open-access online scientific publications, and that data collection was carried out only after obtaining their informed consent.

Additional information

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