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Thomas PROVOT, Xavier CHIEMENTIN, Fabrice BOLAERS, Marcela MUNERA - A time to exhaustion model during prolonged running based on wearable accelerometers - SPORTS BIOMECHANICS - Vol. 20, n°3, p.330-343 - 2019

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A time to exhaustion model during prolonged running based on wearable accelerometers

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ABSTRACT

Defining relationships between running mechanisms and fatigue can be a major asset for optimising training. This article proposes a biomechanical model of time to exhaustion according to indicators derived from accelerometry data collected from the body. Ten volunteers were recruited for this study. The participants were equipped with 3 accelerometers: on the right foot, at the tibia and at the L4-L5 lumbar spine. A running test was performed on a treadmill at 13.5 km/h until exhaustion. Thirty-one variables were deployed during the test. Multiple linear regressions were calculated to explain the time to exhaustion from the indicators calculated on the lumbar, tibia and foot individually and simultaneously. Time to exhaustion was predicted for simultaneous measurement points with $r^2 = 0.792$ and 21 indicators; for the lumbar with $r^2 = 0.568$ and 11 indicators; for the tibia with $r^2 = 558$ and 11 indicators; and for the foot with $r^2 = 0.626$ and 12 indicators. This study allows the accurate modelling of the time to exhaustion during a running-based test using indicators from accelerometer measurements. The individual models highlight that the location of the measurement point is important and that each location provides different information. Future studies should focus on homogeneous populations to improve predictions and errors.

KEYWORDS
Stepwise regression; biomechanical model; sport; fatigue

Introduction

The scientific world defines fatigue during sporting activities as a decrease in the ability to generate a force, couple or imposed power (Billat, 2012). Fatigue from overtraining or stress intensity is considered a major phenomenon in the prevalence of injuries in runners (Mizrahi & Daily, 2012; Patterson, McGrath, & Caulfield, 2011; Voloshin, Mizrahi, Verbitsky, & Isakov, 1998). Moreover, fatigue has often been linked to decreased performance in athletes and can therefore be directly associated with professional outcomes (Nicol, Komi, & Marconnet, 2007a, 2007b; Noakes, 2000). During running, several studies have shown that fatigue, through the risk of injury and the decrease in performance, increases with impact repetition of the foot against the ground (Hreljac, 2004; Milner, Ferber, Pollard, Hamill, & Davis, 2006; Pohl, Mullineaux, Milner, Hamill, & Davis, 2008; Voloshin & Wosk, 1982).

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The effects of these impacts have been largely evaluated with the use of accelerometers. Shorten and Winslow (1992) measured the acceleration on the distal anterio-medial tibia to study the effects of increasing impact on the body. This study was mainly focused on the spectral analysis and the shock attenuation through the body. Similarly, Derrick, Dereu and McLean (2002) studied changes in kinematics and impacts during a test to exhaustion by using an accelerometer placed on the tibia. Results showed that peak leg impact accelerations and impact attenuation increased during the progression of the run to exhaustion. Friesenbichler, Stirling, Federolf and Nigg (2011) examined muscle fatigue by placing an accelerometer on the triceps surae. Authors concluded that the intensity of the vibrations, generated by the repeated impacts, increased with fatigue.

Numerous studies have shown that the measurement of acceleration can provide critical information on running. Accelerations are representative of the running cycle (Lee, Mellifont, & Burkett, 2010; Norris, Kenny, & Anderson, 2016; Purcell, Channells, James, & Barrett, 2005), stride type (Eskofier, Musho, & Schlarb, 2013; Giandolini et al., 2014), shock attenuation (Derrick et al., 2002; Shorten & Winslow, 1992), kinematics of the athlete (Strohrmann, Harms, Kappeler-Setz, & Troster, 2012), excitation frequencies (Friesenbichler et al., 2011; Giandolini, Gimenez, Millet, Morin, & Samozino, 2013) and lower limb stiffness (Buchheit, Gray, & Morin, 2015; Provot, Munera, Bolaers, Vitry, & Chiementin, 2016) and thus allow researchers to study athlete locomotion, technique and performance. These measures were made possible by the development of new, small, light, wearable and low-cost measurement tools. These new sensors allowed not only embedded measurements but also athlete performance monitoring. Although accelerometers have limited measurement capabilities (sampling frequency or magnitude range), many have already been validated for running (Lee et al., 2010; Provot, Chiementin, Oudin, Bolaers, & Murer, 2017).

Fatigue has been studied extensively, and many studies have investigated fatigue by measuring multiple parameters (Nicol et al., 2007a, 2007b). Noakes (2000) emphasised that unique expressions of fatigue (e.g., muscular fatigue, energetic fatigue, cardiovascular fatigue and psychological fatigue) are often limited and that the phenomenon of fatigue is often the mutual representation of these different concepts. Thus, to understand the expression of fatigue, several studies have concentrated on modelling exhaustion while running by means of a group of indicators. Exhaustion is then represented as the inability to follow a running rhythm during a specific and punctual test without taking into account the general physical state of the athlete. Gazeau, Koralsztein and Billat (1997) found large correlations between kinematic indicators (mostly computed on angular variables of the lower limbs) and time limit to exhaustion ($r = 0.995$). However, this study focused only on the ultimate limit of the test and did not take into account the progression of the state of exhaustion of the athlete. Candau et al. (1998) studied the energetic cost during running in order to model exhaustion. The energetic cost was described as function of physiological (blood lactate concentration, ventilation, etc.) and mechanical variables (potential and kinematic energy). However, in the same way, the progression of the state of exhaustion is difficult to study, and the relationship between energy cost and the variability of indicators remains unclear. To our knowledge, no modelling of the progression of the state of exhaustion has been proposed using only accelerometer data. The aim of this study is to understand the potential use of accelerometry in the measurement of exhaustion. It is hypothesised that running exhaustion, as well as its evolution, can be described using wearable accelerometers attached to the lumbar spine, tibia and foot.

Methods

Participants

Ten volunteers (5 male and 5 female) were recruited for this study (age: 38.0 ± 11.6 years; height: 1.73 ± 0.10 m; mass: 66.3 ± 12.6 kg). Each volunteer was a recreational runner with a training frequency of 2 sessions per week. The participants were recruited based on having a consistent running schedule, a respect for medical recommendations for the practice of running in competition and a recent personal competition record for a 10-km (under 45 min) or half-marathon race (under 1 h 40 min). All the procedures were reviewed and approved by the University of Reims Champagne Ardenne local research ethics committee prior to beginning the study.

Protocol

All the participants were fitted with 3 inertial measurement units (IMU Hikob Fox, Villeurbanne, France dimensions: 45 × 36 × 17 mm, mass: 22 g) equipped with a high-frequency tri-axial accelerometer validated for running assessments (Provot et al., 2017). The first device was attached to the dorsal surface of the right shoe above the metatarsals. The second was mounted near the centre of mass of the leg, according to the anthropometric data described by Winter (2009), on the protruding part (mid-shaft) of the tibia. The last device was placed on the trunk near the L4-L5 space of the lumbar spine on the line between the 2 iliac crests (Figure 1). For the first device, 1 axis of the IMU was directed forward of the foot to approach the anteroposterior axis of the segment, for the second and third devices, 1 axis of the IMU was aligned with the longitudinal axis of the segment. Data were collected at a sampling frequency of 1344 Hz with maximum magnitude of ± 24 g for the foot and tibia devices and ± 8 g for the lumbar device. The foot device was mounted on the lace in the eyelets of the housings. Tibia and lumbar devices were secured using a Velcro strip made for the test along with a medical elastic band to avoid slippage on the skin. All the raw data were saved on a memory card. The 3 IMU were synchronised using a radio frequency remote control. The running tests were performed on a treadmill (NordicTrack C300, Logan, UT, USA). To avoid any effects of the equipment, all the participants were asked to wear similar appropriately sized running shoes (Kalenji, Ekiden One, Villeneuve-d'Ascq, France) and socks. During the study, the participants' heart rate was monitored using a heart rate strap (Polar, Kempele, Finland).

Before the running test, the participants performed a 10-min warm-up running at 10 km/h. All the participants were informed that no refuelling would be possible during the test (except for the warm-up). The test was conducted at a constant speed of 13.5 km/h until exhaustion. This speed was appropriate for generating exhaustion in the study population based on the speeds at which they completed their previous 10-km or half-marathon races. Exhaustion was defined as the point at which participants were

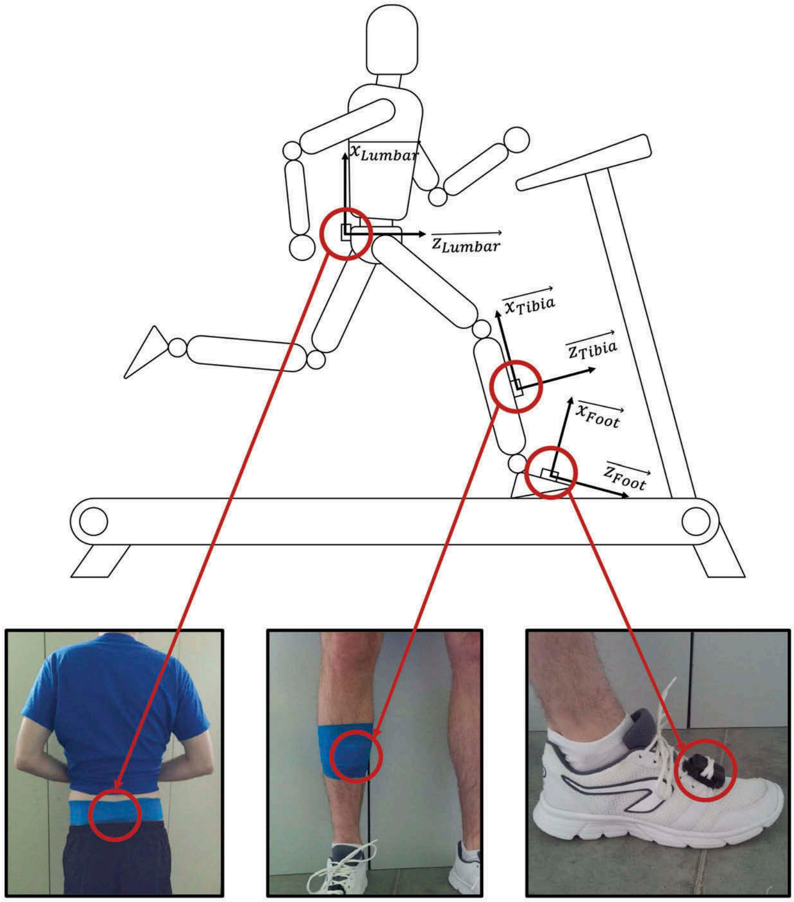

Figure 1. Location of the 3 IMU on the athlete's body. *x*-axis was associated to longitudinal axis of the segments, *y* to medio-lateral and *z* to anteroposterior.

no longer able to maintain the 13.5 km/h running speed. This method was also used by Friesenbichler et al. (2011), and the progression of the state of exhaustion was quantified with a subjective rate proposed by Borg (1982), which presents a linear variation with exercise time considering a constant condition. This method ensures that exhaustion is reached at the end of the protocol. Heart rate was used as an indicator of exertion.

Data processing

Fourteen indicators were computed in this study and divided into 2 groups (Table 1). First, 4 indicators were measured directly from the raw signal (Table 1 Raw). This set of measurements was computed for the 3 accelerometers along different segment axis (longitudinal, medio-lateral and anteroposterior) or for total acceleration. The computed axes were determined by a preliminary study on indicator repeatability. Three of these 4 raw signal indicators were computed in the temporal domain. The first indicator was the root

Table 1. The 14 indicators computed for the time to exhaustion study.

Type	Indicator	Notation	Foot				Tibia				Lumbar			
			Lon	M-L	A-P	Tot	Lon	M-L	A-P	Tot	Lon	M-L	A-P	Tot
Raw	Root mean square	*RMS*	○	-	○	○	○	○	○	○	○	○	○	○
Raw	Past time beyond 3*g*	t_{3g}	-	-	-	○	-	-	-	-	-	-	-	-
Raw	Vibration total value	a_v	-	-	-	○	-	-	-	-	-	-	-	-
Raw	Total energy	*TE*	-	-	○	○	○	-	○	○	○	-	○	○
Stride	Mean stride duration	*MSD*	-	-	-	-	-	-	-	-	○	-	-	-
Stride	Mean stride number	*MSN*	-	-	-	-	-	-	-	-	○	-	-	-
Stride	Mechanical mean contact duration	MCD_m	-	-	-	-	-	-	-	-	○	-	-	-
Stride	Mechanical mean flight duration	MFD_m	-	-	-	-	-	-	-	-	○	-	-	-
Stride	Physiological mean contact duration	MCD_p	-	-	-	-	-	-	-	-	○	-	-	-
Stride	Physiological mean flight duration	MFD_p	-	-	-	-	-	-	-	-	○	-	-	-
Stride	Mechanical vertical stiffness	VK_m	-	-	-	-	-	-	-	-	○	-	-	-
Stride	Physiological vertical stiffness	VK_p	-	-	-	-	-	-	-	-	○	-	-	-
Stride	Mechanical leg stiffness	LK_m	-	-	-	-	-	-	-	-	○	-	-	-
Stride	Physiological leg stiffness	LK_p	-	-	-	-	-	-	-	-	○	-	-	-

Indicators were computed from the acceleration measured on the longitudinal (Lon), anteroposterior (A-P) and medio-lateral (M-L) axis of the human segment as the total acceleration (Tot). ' ○ ' represents the 31 variables determined as repeatable for running and '-' represents non-computed value.

mean square (*RMS*) value, which was used to characterise the magnitude of a varying signal, such as vibration or shock (McGregor, Busa, Yaggie, & Bollt, 2009; Provot et al., 2016). The second indicator was the time spent beyond 3*g* (t_{3g}). This indicator was defined for this study and characterises acceleration over the full test duration. The third indicator was the vibration total value (a_v), defined by the ISO 2631 standard ISO2631 (1997). The indicator was used to characterise the vibration quantity imposed on the human body. The final raw signal indicator was the total energy (*TE*) of the spectrum, defined as the sum of the squared Fast Fourier Transform (Eskofier et al., 2013; Provot et al., 2016).

The remaining 10 indicators were determined from the accelerometry signals of each running stride and then averaged. These indicators were computed only for the longitudinal axis of the lumbar (Table 1 Stride). Two of these 10 indicators, mean stride duration (*MSD*) and mean stride number (*MSN*) contained in the sample, were computed directly from the stride signal (Provot et al., 2016; Purcell et al., 2005). The 8 remaining indicators were computed using decomposed stride signals from 2 phases: a contact phase, where the foot is in contact with the ground, and a flight phase.

According to the literature, there are 2 methodologies for calculating the decomposition of stride signals. First, the decomposition can follow a physical (mechanical) hypothesis that suggests that the contact phase includes the exact moment when the feet is in contact then leave the ground (Blickhan, 1989; Purcell et al., 2005). Decomposition can also follow a physiological hypothesis, whereby the contact phase includes only the exact moment at which the mass of the body is supported by the ground (Cavagna, 1970; Gaudino, Gaudino, Alberti, & Minetti, 2013). The decomposition of each stride on the accelerometer signal was carried using the running phases' description proposed in the study by Gaudino et al. (2013). The 8 indicators were the mean contact duration computed using both the mechanical (MCD_m) and the physiological (MCD_p) hypotheses; the mean flight duration (MFD_m and MFD_p); the vertical stiffness of the leg, defined as the function of the contact and flight durations (VK_m and VK_p) using a uniaxial spring mass model (Dalleau, Belli, Bernard, & Binsinger, 2004); and leg stiffness, defined using a biaxial spring mass model (Morin, Dalleau, Kyro¨l¨ainen, Jeannin, & Belli, 2005) that is a function of the contact and flight durations (LK_m and LK_p). Following the different IMUs and different computed axes, 31 variables were created from the 14 indicators.

Statistical analysis

In this study, running conditions were set as a constant, and the progression of the state of exhaustion was defined as linear with the duration of the test. The progression of the state of exhaustion was represented as a percentage of the maximal duration of the exercise (Friesenbichler et al., 2011; Noakes, 2004). Total exhaustion was considered to be 100% at the end of the test. To study the progression of the 31 variables with the progression of exhaustion, each variable was computed using the accelerometric signal over a sliding unit of 1 min with a recovery rate of 50%. Each variable was standardised to ensure that the progression of exhaustion was measured equally for each participant. Finally, to study the independent behaviour of each variable with the progression of exhaustion and avoid a participant effect, each similar variable for the 10 participants was studied together. The variable Z_j was created to represent the 31 anonymous standardised variables, with $j = 1$ to 31. The progression of Z_j was computed from the 14 indicators and compared to the progression of exhaustion.

A stepwise regression was used to create the progression of exhaustion model using Matlab R2017b (MathWorks, Natick, MA, USA). This algorithm selected variables according to their significance, which was determined using a statistical Fisher test and verified the interdependency of the outcome variable. The model allowed the estimation $\hat{Y}$ of the time before exhaustion as a per cent. $\hat{Y}$ was the function of the different Z_j variables (with $j = 1$ to 31) and coefficients β_j (Equation 1). The validity of the model was judged on 5 criteria: reliability, significance, quality of the prediction, average error and sensitivity.

$$\hat{Y} = \beta_0 + \beta_1.Z_1 + \ldots + \beta_j.Z_j + \ldots + \beta_J.Z_J \quad (1)$$

To analyse the model's reliability, residuals were measured as the difference between the estimated time to exhaustion $\hat{Y}$ and the real time to exhaustion Y. The regression was considered to be adjusted if the residual terms were independent and equally distributed. The normality of the residual terms was determined using a Shapiro–Wilk test, provided that the studied variable was normally distributed and the null hypothesis was rejected if $p_N < 0.05$. Significance was determined using a statistical Fisher test ($p_S < 0.05$), following the null hypothesis that the regression coefficients (β_j) were null. Quality of the prediction and average error were studied between the estimated time to exhaustion $\hat{Y}$ and the real time to exhaustion Y. Quality of the predictions was studied using a Bravais–Pearson test and the determination coefficient r^2. The average error was represented as the root mean square error (RMSE, Equation 2, where L is the sample size). RMSE was expressed in the same units as Y (percentage of the time to exhaustion). To observe the models sensitivity, the same algorithm was used to develop models using only 9 participants following a 'leave-one-out' method. Ten models were created by suppressing 1 of the 10 participants of the panel in each case.

$$RMSE = \sqrt{\frac{1}{L}\sum_{i=1}^{L}\left(Y_i - \widehat{Y}_i\right)^2} \quad (2)$$

Results

The average duration of exercise was 38.5 ± 12.5 min. Figure 2 shows the progression of the averaged subjective Borg rate for the 10 participants according to the percentage of the test duration. This result validates the representation of the progression of exhaustion as a percentage of the maximal duration of exercise.

For the resulting model, only 20 of the 31 variables were selected, reliability and significance were validated, with $p_N = 0.277$ and $p_S < 0.001$. The model results had a coefficient of determination of $r^2 = 0.723$ and an RMSE of 15.4%. The residuals were represented in Figure 3 as a standardised normal distributed variable ($\mathcal{N}(0,1)$). The results of the sensitivity analysis using the 'leave-one-out' method showed that, on average, the suppression of 1 participant in the model resulted in a 0.6% decrease in the RMSE and a 0.02 increase in the determination coefficient associated to the quality of the prediction.

Due to the normality of the residuals (Figure 3), an optimisation of the presented model was created by excluding points falling outside of a tolerance interval equal to 2 times greater than the SD around the M value. The optimised model is presented in Table 2. Twenty-one variables were selected for this new model. The modelling results present a coefficient of determination of $r^2 = 0.792$ and an RMSE of 13.1%. While 21 variables were needed to obtain the best quality of the prediction, using only the first 8 resulted in a coefficient of 0.723, which was equal to the non-optimised model.

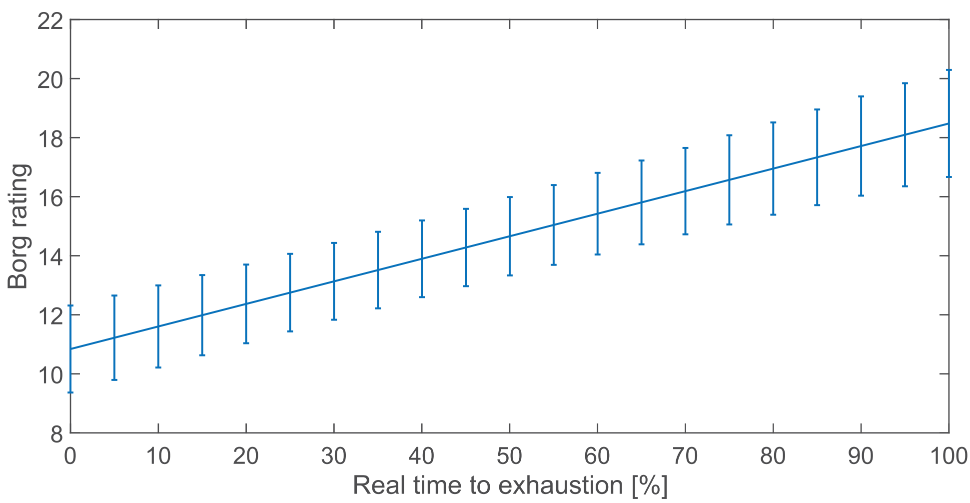

Figure 2. Value of the averaged Borg scale for the 10 participants according to the percentage of the test duration (real time to exhaustion corresponding to Y). The vertical bars represent the SD.

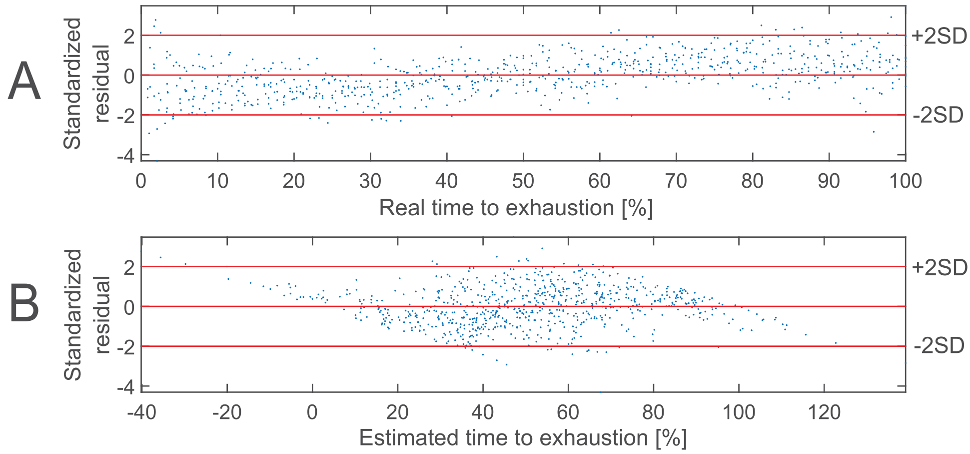

Figure 3. Graphic A presents the residuals distribution as function of the real time to exhaustion (Y) and graphic B, the estimated time to exhaustion ($\hat{Y}$). Residuals are presented standardised, the horizontal lines represent the M value and $\pm$ twice the SD.

Table 2. List of the selected variables for the optimised model according to the algorithm iteration.

Iteration	Indicator	Point	Axis	r^2	β_j
1	*MSD*	Lumbar	Lon	0.311	368.53
2	*RMS*	Foot	A-P	0.471	7.22
3	*MSN*	Lumbar	Lon	0.566	348.15
4	t_{3g}	Foot	Tot	0.607	−7.99
5	*RMS*	Tibia	Tot	0.648	13.75
6	*RMS*	Foot	Tot	0.683	−5.05
7	LK_p	Lumbar	Lon	0.704	−26.13
8	*TE*	Lumbar	A-P	0.723	6.44
9	MFD_p	Lumbar	Lon	0.741	−6.96
10	VK_p	Lumbar	Lon	0.755	27.19
11	*RMS*	Lumbar	M-L	0.763	3.65
12	*TE*	Tibia	Lon	0.770	−7.07
13	*RMS*	Foot	Lon	0.774	3.31
14	MFD_m	Lumbar	Lon	0.777	3.89
15	LK_m	Lumbar	Lon	0.780	−4.36
16	*TE*	Foot	A-P	0.782	5.67
17	*av*	Foot	Tot	0.785	−3.03
18	*RMS*	Tibia	Lon	0.787	2.90
19	VK_m	Lumbar	Lon	0.789	8.16
20	*RMS*	Tibia	M-L	0.791	−4.61
21	*TE*	Lumbar	Tot	0.792	−2.13
	β_0				50.81

The variables were selected from different indicators: mean stride duration (*MSD*), root mean square (*RMS*), mean stride number (*MSN*), past time beyond 3*g* (t_{3g}), physiological leg stiffness (LK_p), total energy (*TE*), physiological mean flight duration (MFD_p), physiological vertical stiffness (VK_p), mechanical mean flight duration (MFD_m), mechanical leg stiffness (LK_m), vibration total value (*av*) and mechanical vertical stiffness (VK_m). The formula expressing the percentage of total exhaustion is represented as the sum of the different indicators multiplied by their respective coefficients β_j. Indicators were computed from the acceleration measured on the longitudinal (Lon), anteroposterior (A-P) and medio-lateral (M-L) axis of the human segment as the total acceleration (Tot). β_0 indicator represents a constant of the model.

Finally, to evaluate which measurement site provided the most information on exhaustion, 3 models were developed using the indicators associated with only the foot, tibia or lumbar. For the lumbar, 11 variables were selected, and 11 iterations were

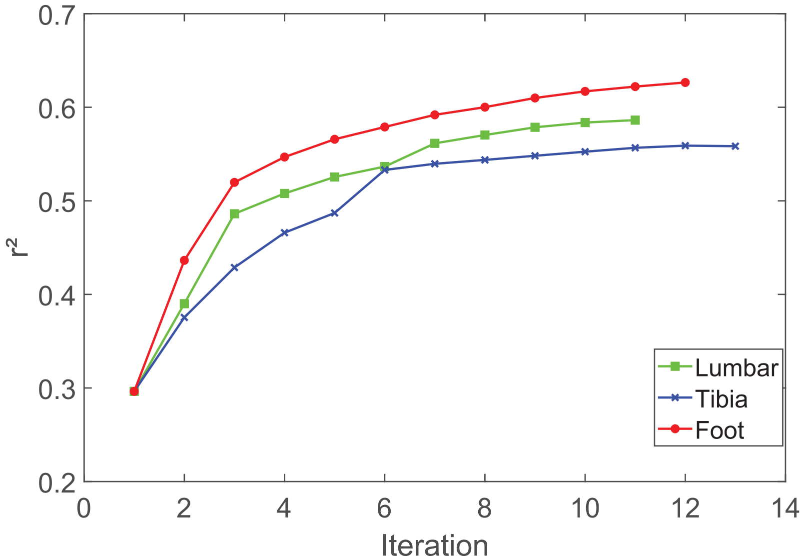

Figure 4. Evolution of the determination coefficient for the proposed models (foot, tibia and lumbar model) as function of the iteration number of the algorithm.

performed to reach a final determination coefficient of $r^2 = 0.586$ with an RMSE of 18.71%. The model was significant ($p_S < 0.001$) but not reliable ($p_N = 0.021$). For the tibia, 11 variables were selected, and 13 iterations were performed to reach a final determination coefficient of $r^2 = 0.558$ with an RMSE of 19.34%. The model was both significant ($p_S < 0.001$) and reliable ($p_N = 0.276$). For the foot, 12 variables were selected, and 12 iterations were performed to reach a final determination coefficient of $r^2 = 0.626$ with an RMSE of 17.79%. The model was significant ($p_S < 0.001$) but not reliable ($p_N = 1.87E-04$). The progression of the determination coefficients of the models as a function of the iteration number is presented in Figure 4.

Discussion and implications

This work proposed a significant and reliable method for modelling the time to exhaustion by using accelerometry indicators. The optimised model reached a determination coefficient of $r^2 = 0.792$, thus representing a large component of the evolution of exhaustion, providing various indicators representing running technique, perceived vibrations and shocks, the energy required for movement and the stiffness of the lower limbs. The inclusion of additional variables could provide substantial information to the model to explain the variability that was not accounted for by the accelerometer data. These results reinforce the conclusion of Noakes (2000) that fatigue must be expressed in a multidisciplinary manner. As proposed by Gazeau et al. (1997) and Candau et al. (1998), kinematic or physiological variables that are directly related to energy cost can be integrated into modelling to achieve better quality of the prediction.

The sensitivity analyses on the number of participants showed that suppressing 1 person tended to improve the quality of the prediction and reduce the error in the model. These results may have been affected by the heterogeneity of the study population, which is highlighted by the variation in the results of each participant (38.5 ± 12.5 min). This notion was confirmed in a study by Saunders, Pyne, Telford and Hawley (2004). Indeed, the morphological differences of the participants (90.6 kg for 1.92 m and 48.9 kg for 1.60 m for the 2 extreme participants) seemed to impact the mechanisms of exhaustion during running. However, reducing the size of the population tested tended to personalise the model and reduce the variability in the sample. The advantage of a personalised model is that it could adapt according to the evolution of the performance of the athlete. Each new test session could then feed the model to improve the quality of the prediction that can evolve depending on the training.

Although, modelling is sensitive to the number of participants. The removal of statistically extreme values allowed the optimisation of the model to suppress biases. The optimised model (based on 21 indicators rather than 20 for the non-optimised model) increased the quality of the prediction by 0.095 and decreased the RMSE by 2.3%. However, the error was still large (15.4% before, 13.1% after) in estimating time to exhaustion. A review of the model suggests that indicators rapidly integrated into the models presented the strongest determination coefficients with the evolution of exhaustion and provided very different information on the activity of running.

First, indicators associated with stride, such as the *MSD*, represented 31.1% of the information about the progression of exhaustion in the optimised model. This information supports the results of numerous studies that have observed a decrease in stride frequency (and thus an increase in duration) with the onset of fatigue (Dutto & Smith, 2002; Mizrahi, Verbitsky, Isakov, & Daily, 2000). However, a study by Schache et al. (2001) demonstrated that the temporal parameters of foot strike showed significant differences between treadmill and over-ground running; thus, the progression of these parameters with the progression of exhaustion could differ under real race conditions. Nevertheless, Morin, Jeannin, Chevallier and Belli (2006) observed a similar variation in the time parameters associated with fatigue from repeated sprints at variable speeds.

Other indicators that contributed to the model were representative of the vibration and shock perceived by the athlete (*RMS*, t_{3g}, *TE*). These indicators increased the quality of the prediction of the optimised model to 0.723 in the first 8 iterations. These results confirm those of Friesenbichler et al. (2011), who observed an increase in the amplitude of vibrations (directly related to *RMS*) with exhaustion. *TE* at the lumbar level on the anteroposterior axis was also among these indicators. This variable can be interpreted as the amount of energy needed to move the centre of mass of the body forward. The place of this indicator in the model can be confirmed by a study of the energy of exhaustion proposed by Candau et al. (1998). They observed a significant increase (17%) in mechanical energy cost with the onset of exhaustion.

Finally, the model also included indicators of stiffness of the lower limbs, particularly LK_p, which has been shown by several studies to be significantly sensitive to exhaustion (Dutto & Smith, 2002; Morin et al., 2005).

This work allowed also the study of the progression of exhaustion at different measurement points. The results showed that the model developed for the foot had a faster and stronger convergence than did the lumbar or tibial models. The models could also be compared by looking at the variables included during the first iterations of the algorithm (variables contributing the most to the improvement of the quality of the prediction). This type of comparison demonstrated that the model of the lumbar presented information in terms of the foot strike technique, which was consistent with a study by Lee et al. (2010), but not in terms of perceived shocks or vibrations. The model developed for the foot presented information in terms of both perceived impact (with such indicators as *RMS* and t_{3g}) and foot strike technique (as shown in the studies by Giandolini et al. (2013, 2014)), which could explain why it had the best convergence. The lack of information on the impact at the lumbar site is explained by the body's capacity for attenuation, which was highlighted in a study by Shorten and Winslow (1992). However, although both the foot and the lumbar models were not found to be reliable, these models still provide some understanding of the information measured on the body.

Following these results, future studies may propose different model improvements. This study highlighted that the measurement point is important for modelling. Measurements from different sensor locations do not necessarily provide the same information. One approach to improving the model would be to use additional measuring points to obtain more information on exhaustion. However, additional measuring points cannot always be incorporated due to comfort constraints that can affect athlete performance. Another approach would then be to multiply the sensors on a single measurement point as proposed in the study of Buchheit et al. (2015). The use of the other sensors of the inertial units or physiological sensors could then provide additional relevant information to develop specific indicators and optimise the time to exhaustion model. Moreover, the advantage of a single measurement point would be to use a light and compact measuring system to measure the information in real conditions on the athlete.

This model can also offer direct practical applications. Provided that it is possible to capture, process data and communicate the progression of exhaustion in real time, the athlete would be able to adapt his effort and optimise his performance. This model could be used to predict physical break phenomena during physical activity. Doing so could help athletes to manage their efforts by indicating the time duration remaining before they reach total exhaustion. In addition, coupled with a risk criterion (e.g., limit percentage not to be exceeded), the model could avoid extreme efforts during which the probability of injury is important. However, this would require further study of the correlation between exhaustion and injury.

Finally, the model developed in this study presents certain limitations. The description of a linear evolution of the exhaustion progression occurs only for constant conditions that are generally difficult to maintain during the practice of a sport. Moreover, in addition to the problem of the heterogeneity of the population tested, the data used for the creation of this model came from data collected in the laboratory that differs very much from the real conditions (Schache et al., 2001). If the model developed gives an estimate of the state of exhaustion, several points of improvement remain necessary to make the use of the exhaustion model more reliable.

Conclusions

This work proposed a significant and reliable method for modelling the time to exhaustion by using accelerometry indicators. The proposed model reached a determination coefficient of up to 0.792 and thus accounted for a large part of the progression of exhaustion. These positive results can be explained by the chosen definition of exhaustion, which used indicators that represented running technique, perceived vibrations and shocks, the energy required for movement and the stiffness of the lower limbs.

This study also highlighted that precision seems to be directly related to the panel of participants studied. The study of a heterogeneous population does not seem to lead to a general modelling of time to exhaustion. The mechanisms of exhaustion seem to be influenced by the morphology of the athletes. One improvement in future research could be to conduct a similar study on a homogeneous panel of runners. However, this methodology does not account for the evolution of the athletes. A different approach would be to study time to exhaustion in a single athlete. This perspective would allow the development of an auto-adaptive model. In this case, the exhaustion test could be performed at several different speeds to determine whether the model can be interpolated according to running speed.

Disclosure statement

No potential conflict of interest was reported by the authors.

Funding

These investigations were financially supported by the Champagne-Ardenne region and the European Fund of Regional Development (FEDER).

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