Kronos 2017: 16(2)
ISSN: 1579-5225 - e-ISSN: 2603-9052
Bastida Castillo, Alejandro., Gómez Carmona, Carlos David., Pino Ortega, José.
Relación Entre la Entropía Aproximada y la Pérdida de Velocidad Media Propulsiva Durante el Ejercicio de Media Sentadilla.

Sport Performance

Relación Entre la Entropía Aproximada y la Pérdida de Velocidad Media Propulsiva Durante el Ejercicio de Media Sentadilla

Relationship Between Aproximate Entropy and Mean Propulsive Velocity Loss During Half Squat Exercise

Bastida Castillo, Alejandro.[1], Gómez Carmona, Carlos David.[2], Pino Ortega, José.[1]

[1]*BioVetMed & SportSci. Departamento de actividad física y deporte, Universidad de Murcia, Murcia, España*
[2]*Training Optimization and Sports Performance Research Group (GOERD), Departamento de música, plástica y expresión corporal, Universidad de Extremadura, Cáceres, España*

Dirección de contacto:
Alejandro Bastida Castillo
Fecha de recepción: 16 de mayo de 2017
Fecha de aceptación: 16 de noviembre de 2017

RESUMEN

Hoy en día, hay un interés creciente en el estudio de los mecanismos producidos durante el entrenamiento de la fuerza. La pérdida de velocidad media propulsiva (VMP) ha sido ampliamente utilizada por entrenadores y científicos deportivos en el control del entrenamiento de la fuerza. El objetivo del presente estudio fue analizar la relación entre la pérdida VMP y la entropía aproximada (ApEn), y demostrar su validez como indicador del entrenamiento de la fuerza. Once varones bien entrenados participaron voluntariamente en este estudio. Los sujetos fueron sometidos a cuatro series de 10 repeticiones del ejercicio de sentadilla en máquina Smith. La intensidad fue del 65% 1RM y 60% del carácter del esfuerzo. Durante la ejecución del ejercicio, VMP y ApEn fueron monitorizados continuamente con una frecuencia de muestreo de 1000Hz mediante dispositivo inercial WIMU PROTM (Sistemas RealTrack, Almería, España). Los resultados muestran que ambas variables (VMP y ApEn) siguen la misma tendencia, lo que sugiere que ApEn es un método válido para la cuantificación de la fatiga local y podría ayudar a comprender el complejo comportamiento muscular durante el entrenamiento de la fuerza.

Palabras Clave: muscular fatigue, strength training, ApEn entropy

ABSTRACT

Nowadays, there is an increasing interest in the study of mechanisms produced during strength training. Mean propulsive velocity loss has been widely used by trainers and sports scientists in strength training control. The aim of the present study was to analyze the relationship between mean propulsive velocity loss and approximate entropy, and to prove its validity as an indicator of strength training. Eleven trained men participated voluntarily in this study. Subjects were submitted to four series of 10 repetitions of squats exercise on the Smith machine. The intensity was 65% 1RM and 60% level of effort (LE). During experimental trails, mean propulsive velocity (MPV) and approximate entropy (ApEn) were monitoring continuously with a 1000Hz sampling frequency by WIMU PROTM inertial device (RealTrack Systems, Almeria AND, Spain). Results show that both variables (entropy and mean propulsive velocity loss) follow the same tendency, suggesting ApEn to be a potential valid method for local fatigue quantification and complexity muscular behavior during strength training.

Keywords: muscular fatigue, strength training, ApEn entropy

INTRODUCTION

Nowadays, there is an increasing interest in the study of mechanisms produced during the strength training (ST). The problem is that many aspects related to this type of exercise in humans are still unclear. (Badillo y Serna, 2002). This lack of clarity is due to the interaction of multiple combinations of variables on ST joined to the complex access needed to research these variables, which in many cases requires an in motion observation (Wilmore y Costill, 2007). Local, peripheral or muscular fatigue (LF) is one of the most analyzed indicator in the exercise physiology area, and, although it is well known, it has not been well defined and understood (Ferrari, Mottola, & Quaresima, 2004; Gómez-Campos, Cossio-Bolaños, Brousett Minaya, & Hochmuller-Fogaca, 2010). LF is an important variable on the training control in order to maximize the physiological adaptations and to avoid overtraining in high level athletes (García-Pallarés & Izquierdo, 2011). Sánchez-Medina & González-Badillo, (2011) validated the use of mean propulsive velocity loss (MPVL) to objectively quantify the LF during the ST. Because of this research, MPVL has been widely used by trainers and sport scientists in the ST control. Therefore, Pareja-Blanco, Sánchez-Medina, Suárez-Arrones, & González-Badillo (2016), consider this variable's monitoring during a ST program an effective method to estimate muscular damage, hormonal response and fatigue, among others, while being a non-invasive method. Equally, it has been found better strength increase on the group with less MPVL on the ST (15% against a 30%). Thereby, it seems desirable to keep a moderated fatigue state during the ST, not only to avoid overtraining and reduce the quantity and quality of training (García-Pallarés & Izquierdo, 2011), but also to achieve an improvement in the physical-sporting performance (Pareja-Blanco et al., 2016).

On the other hand, all biological systems present complex and irregular fluctuations that cannot be analyzed by conventional statistical techniques, being that they give a very limited information on their behavior. West, Rigney, & Goldberger, (1990) explain that this is because organisms follow a chaotic and very flexible model, which operate away from equilibrium so that they behave like complex systems ruled by non-lineal dynamics. Usually lineal analytic approaches has been used for the study of physiological parameters. Although recently, there has been an increasing interest in the use of non-lineal analytic techniques (McGregor, Armstrong, Yaggie, Bollt, et al., 2011). In the field of non-lineal dynamic systems analysis, there are many tools that can give valuable information regarding the accelerometric signals analysis (Parshad, McGregor, Busa, Skufca, & Bollt, 2012). In particular, tools referred as entropy (regularity statistics) have been applied to the march analysis (McGregor, Armstrong, Yaggie, Parshad, & Bollt, 2011; Parshad et al., 2012) or postural control (Busa, Jones, Hamill, & van Emmerik, 2016; Busa & van Emmerik, 2016; McGregor, Armstrong, Yaggie, Bollt, et al., 2011). Entropy has been conceptualized from the thermodynamics area, under processes with fluctuations, instability and evolution (Dincer & Cengel, 2001). Entropy quantifies the regularity of a time series (Pincus, 1991). A less complex system corresponding with a less adaptive system and therefore a lower entropy value (Orellana & Torres, 2010). This lower values of entropy Nowadays, entropy application supposes a different analysis perspective that can provide interesting information for the muscular behavior, and biological and physiological signals investigations in general (Orellana & Torres, 2010).

Therefore, this study has the objective of checking the existing relationship between MPVL and ApEn entropy reported on the accelerometric signal, and to prove its validity as an indicator of fatigue in ST. The work hypothesis is that as the MPVL increases, ApEn decreases, in other words, the more fatigued is de athlete's body (higher MPVL values), more regular will be his performance (lower ApEn values).

METHOD

Participants

Eleven trained men participated voluntarily in this study. All participants had at least two years of experience on ST, did not present any health problems and had a normalized strength on the squat exercise (relation between 1RM and their body weight) superior than 1.5, meaning they could perform one repetition with a supplementary load of 150% of their body weight. In table 1, anthropometric, physiological and strength assessment data measured in participants are shown. These data were obtained with a wall height rod (SECA, Hamburg, Germany) and a body composition monitor model BC-601 (TANITA, Tokyo, Japan).

Table 1. *Anthropometric, physiological and strength assessment of the participant subjects.*

Subject	Strength Assessment		Anthropometric			Physiologic				
	Average 1RM	NS (Ratio)	Height	Weight	BMI	LBM (%)	LBM (kg)	FM (%)	FM (kg)	W (%)
1	110	1,56	1,70	70,50	24,39	82	59,00	14	9,08	67
2	135	1,76	1,76	76,50	24,70	84	74,40	12	10,17	63
3	110	1,90	1,71	57,80	19,77	76	51,40	20	13,63	59
4	130	1,62	1,73	80,20	26,80	81	59,50	15	11,14	61
5	140	1,94	1,77	72,00	22,98	84	67,20	11	9,09	65
6	130	1,82	1,72	71,60	24,20	79	66,20	17	10,67	59
7	120	1,53	1,84	78,40	23,16	82	73,60	14	12,51	69
8	140	1,87	1,79	75,00	23,41	74	64,10	18	8,42	63
9	135	1,76	1,77	76,70	24,48	87	53,00	7	4,53	50
10	180	1,93	1,89	93,50	26,18	76	67,60	20	15,64	58
11	190	2,02	1,74	94,20	31,11	76	60,50	21	16,50	56
Average	138,18	1,79	1,77	76,95	24,65	80	63,32	15	11,03	61
Deviation	25,52	0,16	0,06	10,25	2,82	0,04	7,14	0,04	3,64	0,03

Note. *1RM: 1 repetition maximum; NS normalized strength (ratio between the weight and the 1RM in the squat exercise); BMI: Body mass index; LBM: Lean Body Mass; FM: Fat mass; W: Water.*

All subjects were informed about the study procedures and their possible risks, giving their consent to participate before testing. Subjects do not consume alcohol or caffeine the day before the test and can't practice high intensity physical activity either. The study was approved by the ethics committee of the University of Murcia.

Instruments

To MPV and entropy monitoring in this research, a inertial device calledWIMU PROTM (RealTrack Systems, Almeria AND, Spain) was used. This device contains 4 3D accelerometers among other sensors (3 3D gyroscopes with a 2000 grades/second full-scale output range, a 3D magnetometer, a 10 Hz GNSS, a UWB, etc.) that detects and measures movement using a micro-electromechanical system with an adjustable sample frequency from 10 to 1000 Hz. The full-scale output range is ±16 g in 3 accelerometers and ±100 g in the remaining accelerometer. Each device has its own 1 Ghz microprocessor, 8 GB flash memory and high-speed USB interface, to record, store and upload data. The device is powered by an internal battery with 4h of life, weights 65 g and is 81x45x16 mm in dimension.

To monitor the MPV, the acceleration measured by 3 triaxial accelerometers, which compose this device, was employed. From the acceleration, the device estimates the mean propulsive velocity of each repetition in the concentric and eccentric phases both. In this research, the mean propulsive velocity loss of the concentric phase was used as a variable. In addition, the raw acceleration data were used to determine entropy variable through ApEn calculation. Validity and reliability of the WIMU PROTM to MPV measurement has been shown in a paper pending of publication (Muyor, 2018). Each trial was downloaded using the manufacturer's software S PROTM (RealTrack Systems, Almeria AND, Spain) to obtain MPV and

ApEn value of each repetition.

Procedures

Subjects went only once to the lab where they were performed 4 series of 10 repetitions of half squat exercise on the Smith machine (Technogym, Cesena, Italy) until 90º flexure with a complete stop, in order to suppress the possibility of rebound and improve the reliability (Pallarés et al., 2014). The intensity was of 65% of the first 1RM and the 60% of the “level of effort”. For the supplementary weight calibrated discs of 2.5, 5, 10 and 20 kg (Salter, Barcelona, Spain) were used. During experimental trials, MPV was continuously monitored by a WIMU PROTM inertial device with a 1000Hz sampling frequency. The inertial device was fixed on the center of the bar using adhesive tape (Figure 1) to avoid the influence of noise produced by the guiderails on the data measurement.

Figure 1. *Inertial device location before and during the execution of the exercise.*

Familiarization and 1RM test

The squat was used because of its dynamic and multiarticular character, besides its usage both in health programs and in physical-sport performance. The squat exercise was performed following the next specifics (Rodriguez, 2008): (I) locate the body under the Smith machine, (II) take the bar using a prone grip, with a separation slightly wider than the shoulders, (III) the bar rests on the trapeze and the feet are placed apart as wide as the shoulders (with no rotation), (IV) the back is held in its natural curve during all the movement meanwhile the eyes look up front, (V) flexure at a controlled speed until reaching a 90º angle (each subject was determined by lateral supports previous to the 1RM assessment), (VI) without balancing, the subject extends at maximum velocity until reaching starting position. Subjects were familiarized with the procedure and measurement instruments before the assessment. For the 1RM measurement, a general warm up (5 min on a cycle-ergometer at moderate intensity) and a specific warm up (3 series of 8 repetitions at the 40% of the 1RM with the characteristics mentioned before) were done. Mean propulsive velocity (MPV) monitoring allowed a 1RM estimation of every one of the subjects from their first repetition, estimating their 70% of the 1RM from the MPV of the last two warm up repetitions. Using this estimation, the load was progressively increased until reaching a load in which their MPV was around 80% of the 1RM (0.44 ± 0.04 m/s) (Data not published). This progressive increase until the 80% 1RM was chosen because from this percentage, nearly 100% of the motion execution is within the propulsive phase and the 1RM estimation has a very low error (Sanchez-Medina, Perez, & Gonzalez-Badillo, 2010). The 100% of the motion execution is within the propulsive phase when percentage of 1RM is higher than 90% 1RM (Sánchez-Medina, Pallarés, Pérez, Morán-Navarro, & González-Badillo, 2017)

Variables

Mean Propulsive Velocity Loss

This variable determines the difference between the MPV of the fastest repetition and the MPV of the slowest one, which, in all analyzed cases, is the last repetition performed by the subject in the different series. This is expressed in a percentage and to do it, the following formula is employed (Figure 2) where MPVmax is the mean propulsive velocity of the fastest repetition and MPVmin is the mean/average propulsive velocity of the slowest one.

$$\frac{MPV_{max} - MPV_{min}}{MPV_{max}} * 100$$

Figure 2. *Formula used for mean propulsive velocity loss calculations during the different series performed during the research*

Entropy

Entropy is an abstract concept, difficult to comprehend in order to apply it on statistical calculations, due to its origin being in the thermodynamics area, and as a bridge helping the discovery of concepts such as reversibility and irreversibility of process happening to a system (Dincer & Cengel, 2001). Until then, under the perspective of classical science, a natural equilibrium and stability vision existed. Nowadays, entropy formulation is vital to understand certain aspects of thermodynamics such as order evolution (West et al., 1990).

Therefore, entropy quantifies the regularity of a time series (Pincus, 1991) that, in the case of this study, is the signal that the inertial device accelerometer reports when the subject performs the repetitions. Entropy says that the most predictable a series is, less complex it will be, corresponding with a less adaptive system and therefore a lower entropy value (Orellana & Torres, 2010). Under this concept, aging has been linked to low entropy, same as pathological systems that show lower entropies than healthy systems (Goldberger, Peng, & Lipsitz, 2002). So, this investigation suggests that entropy could be linked with other physiological and biological processes of the human body, such as fatigue and overtraining. There exist three algorithms to calculate entropy: the approximated entropy (ApEn) as a measure to quantify the regularity of a temporal series, knowing that a series is regular if there are repetitive patterns in it (Pincus, 1991, 2001; Pincus & Huang, 1992), sample entropy (SampEn) that corrects some errors brought by the ApEn. Since the ApEn compares every pattern with itself, it is suggested that in a temporal series there is more similarities than the ones that really exist (Richman & Moorman, 2000) and the multiscale entropy (MSE) that was introduced in order to deal with the calculation in superior scales, due to the ApEn and SampEn being calculated on a unique scale (Costa, Goldberger, & Peng, 2002). In this research the ApEn was used, applying its calculation on the whole inertial device accelerometer's signal of the series repetition performance.

$$ApEn(m,r,N) = ApEn(m,r) = \phi^m(r) - \phi^{m+1}(r)$$

$$\phi^m(r) = (1/N-m+1)\sum_{i=1}^{N-m+1} \ln C_r^m(i)$$

$$C_r^m(i) = N^m(i)/(N-m+1)$$

Figura 3. *Fórmula para calcular la entropía aproximada (ApEn) y las variables para el cálculo de la ApEn.*

Data Analysis

First of all, a descriptive analysis of the sample through the mean and standard deviation was realised. Then, an exploratory analysis of the data was done in order to check the distribution of them. After this analysis, a variance test (ANOVA) was used to identify the differences between the performed series averages. The Bonferroni post-hoc adjust was used for the two on two comparisons (Field, 2009). The effect size was calculated through Cohen's D, reporting means differences and confidence intervals. Finally, a linear regression test was done to check the relationships between MPVL and ApEn. These data were treated using SPSS v23.0 (IBM Corporation, Somers, USA). Significance was stablished in $p<0.05$.

RESULTS

On table 2, the mean, and standard deviation of the entropy and MPVL reported in function of the different performed series is shown. The results of the mean difference analysis with the Bonferroni correction and the effect size through Cohen's D, can be seen on table 3. Figure 4 shows the mean difference and the confidence intervals of the post-hoc analysis for each series comparison.

Tabla 2. *Means, Standard deviation of ApEn y MPV reported in different series.*

Series	Entropy	MPV (%)
1	0,53±0,03	21,60±0,40
2	0,51±0,03	23,39±1,07
3	0,48±0,03	26,98±1.97
4	0,44±0,04	30,24±2,32
Mean	0,49±0,05	25,57±3,71

Table 3. *Univariate Differences, Mean Differences, 95% interval confidence and effect size of post-hoc comparison in different bouts.*

	1 vs 2					1 vs 3					1 vs 4				
	p	*MD*	*95%CI*		*ES*	*p*	*MD*	*95%CI*		*ES*	*p*	*MD*	*95%CI*		*ES*
			L	*U*				*L*	*U*				*L*	*U*	
ApEn	.34	0.02	-0.01	0.07	0.66	.00**	0.05	0.01	0.10	1.66	.00**	0.09	0.05	0.13	2.54
MPV	.08*	-0.07	-0.03	0.00	2.17	.00**	-0.05	-0.07	-0.03	3.41	.00**	-0.08	-0.10	-0.06	5.21

	2 vs 3					2 vs 4					3 vs 4				
	p	*MD*	*95%CI*		*ES*	*p*	*MD*	*95%CI*		*ES*	*p*	*MD*	*95%CI*		*ES*
			L	*U*				*L*	*U*				*L*	*U*	
ApEn	.29	0.03	-0.01	0.07	1	.00**	0.06	0.02	0.10	1.98	.15	0.03	-0.00	0.07	1.13
MPV	.00**	-0.03	-0.05	-0.01	2.07	.00**	-0.06	-0.08	-0.04	3.77	.00**	-0.03	-0.05	-0.01	1.42

**p≤..05; **p≤..01; MD: Mean Difference; CI: Confidence Interval; U: Upper L: Lower;*

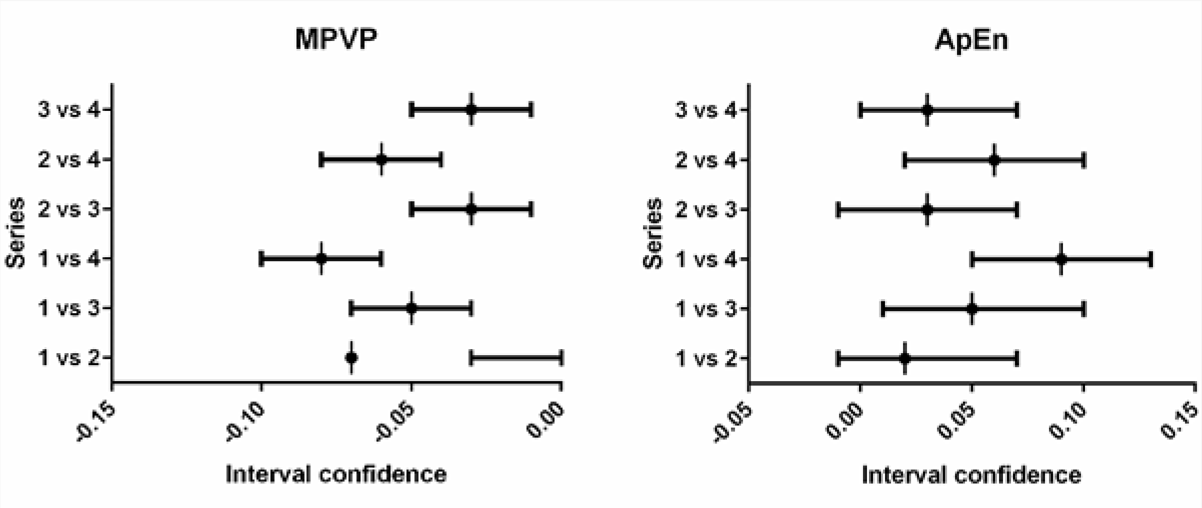

Figura 4. *Mean Difference and Interval confidence of post hoc analysis in MPVP and ApEn.*

On table 2 and 3 there is a descent in the mean entropy value associated with the performed series, as well as an increase of the MPVL. Data show statistically significant differences among the different series. In the post-hoc differences between series 1 and 3, 1 and 4, and 2 and 4 in the ApEn variable were examined. Equally, MPVL showed significant differences according to the performed series, being series 1 and 2 the only combination that shows no signification. Cohen's D show big effect sizes in all comparisons (D>0.80).

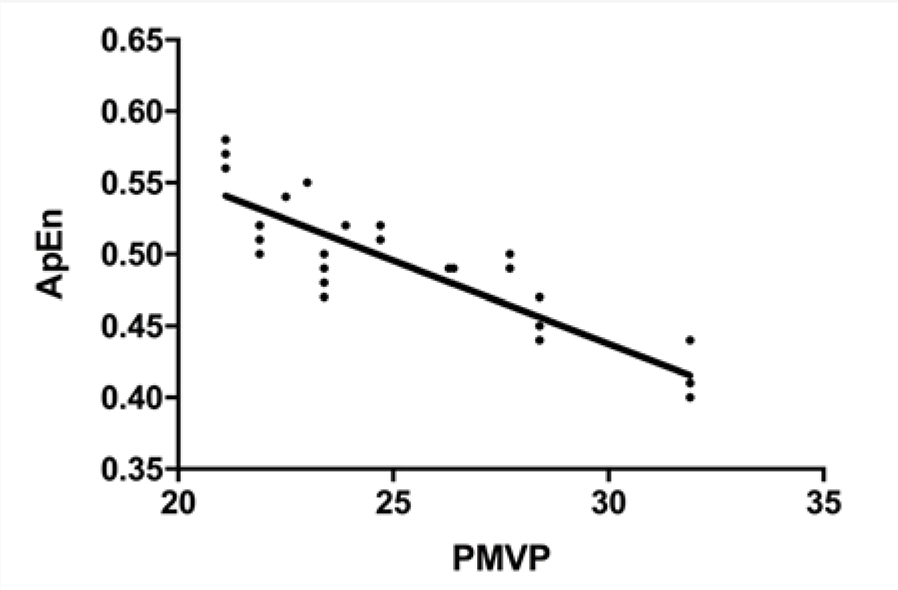

Figure 5. *Linear regression of PMVP and ApEn.*

Finally, Spearman correlation test was done to examine the relationship between entropy and MPVL (Figure 5). Results show an inversely proportional relation with an r value of r=-0.8952 (p<0.0001).

DISCUSSION

As far as we know, although some studies have applied the entropy calculations over an accelerometric signal under other stimuli (Busa et al., 2016; Busa & van Emmerik, 2016; McGregor, Armstrong, Yaggie, Parshad, et al., 2011; Parshad et al., 2012), this is the first study that applies entropy calculation on an accelerometric signal reported from the ST (half squat). In this study, under controlled conditions, an analysis of the half squat exercise was done to evaluate if entropy ApEn could be utilized as an objective indicator of LF induced by typical ST sessions. To do so, MPVL was used as a comparison standard, it has been used as an LF indicator before through its ability to reasonably estimate metabolic stress (Sánchez-Medina & González-Badillo, 2011). Therefore, in the results, it can be checked that both variables (entropy and MPVL) follow the same tendency, approaching entropy ApEn to be a valid method for LF quantification during ST. Equally, results show how the entropy reported value declines with the over the series performed, according to the MPVL (in this study expressed as a loss percentage in the series). Both variables obtained significant differences between sets ($p<0.05$), distinguishing the level of neuromuscular fatigue produced by the execution of the exercise

As it has been explained previously, using non-lineal statistics such as the entropy come from the relationship of the physiological processes behavior that our knowledge cannot grasp yet (Pincus, 2001). Low entropy has been linked with pathological systems (Goldberger et al., 2002). Moreover, ApEn has been used for cardiac frequency analysis, differencing between healthy and sick groups (this last ones with lower entropy values) of newborns (Pincus, 2001) an application that makes more sense each time, since it's evident that traditional statistics can't provide a quality analysis (Orellana & Torres, 2010). In that sense, ApEn has been employed in multiple forms to determine subtle perturbations on hormonal secretion patterns or fisiopathological aging, for many hormones, including insulin (Meneilly, Ryan, Veldhuis, & Elahi, 2011).

In other studies, this calculation has been used in order to quantify the complexity of accelerometric signals (Kaipust, Huisinga, Filipi, & Stergiou, 2012; McGregor, Armstrong, Yaggie, Parshad, et al., 2011; Parshad et al., 2012; Roemmich, Zeilman, Vaillancourt, Okun, & Hass, 2013). McGregor, Busa, Skufca, Yaggie, & Bollt, (2009) identify lower values of entropy on runner subjects after their monitoring using accelerometry on a maximum incremental test. Moreover, during the strength training, as shown by Pareja-Blanco et al., (2016), better strength increase was produced by subjects who only lost 15% of their propulsive velocity. And following García-Pallarés & Izquierdo, (2011) recommend not to get to the failure repetition in order to get a better and faster neuromuscular recovery and to not compromise subsequent strength training sessions. In that matter, ApEn could detect these optimum fatigue points using its bigger sensibility capacity regarding MVPL. Also, in this study has been detected not only an entropy decline during the series (short-term) but during the whole exercise (short-medium term) therefore it is expected that it also happens during a training session. Regarding the later idea, with the identification of the maximum and minimum reported entropy values during a strength training, thresholds could be determined to get a better control of the training and the fatigue. This is explained because a less complex organism or system is in turn less adaptive (Hurd, Morrow, & Kaufman, 2013). In that sense, Kaipust et al., (2012), analyzing the stride during the march using accelerometry, detected that natural fluctuations presents on length and wide of it were more regular and repeatable in patients with multiple sclerosis, concluding that this happens since they have less adaptive response capacity to perturbations during the march.

Under the same logic, it is believed that ApEn is a signal complexity indicator, and, understanding that the signal is less complex as the subject's LF state increases. However, comprehension and application of this concept is still to be discovered. In McGregor, Armstrong, Yaggie, Bollt, et al., (2011) study, where they use this statistic applied to postural control, contradictory data is obtained in which complexity increases with fatigue, although in different conditions than ST.

As a conclusion, in this document it has been checked a relationship between ApEn entropy with a fatigue indicator during strength training controlling MPVL. Therefore, conceptually, following the chaotic model, neuromuscular fatigue state could be similar to the pathological one, since it has a lesser degree of complexity and hence, being less adaptive.

PRACTICAL APPLICATIONS AND FUTURE RESEARCH PROPOSALS

MPVL has been utilized for training control and fatigue control during strength training. And different studies endorse the validity and reliability of this variable usage for those purposes (REF). Although, in this document the ApEn variable has been introduced, which has been getting a lot of studies in which it gets a bio-medical area application. Force-velocity analysis can be valid, although, treatment of a statistic such as ApEn possibly has a a higher measurement sensibility such as being able to detect neuromuscular fatigue, and even the distinct phases of it that are being discovered, being useful, this statistic, not only for training control, but for the complex muscular behavior study.

The different scientific areas share more methodologies, technologies, concepts, etc., over time, enriching their research systems, and helping understanding each other. Recently, there is work being carried out with this new entropy concept, being known as a quantifier of the complexity and uncertainty of a system. It seems to be some relations between entropy and diverse physiological processes, such as the LF here mentioned. Therefore, through the data obtained, it is suspected that ApEn has an important role of the calculation to get the comprehension of the complex muscular behavior. This study has shown ApEn as a quick fatigue indicator for training and, also, to research thoroughly the muscular response to determined stimuli during ST. Then, multi variant entropy quantification seems necessary on future researches. Among them, it should be useful check its behavior under different stimuli such as: different exercises, intensities, previous fatigue levels; contrasted with biomarkers, with subjects of different training levels and under monitor of different technologies such as NIRS, electromyography, inertial devices, etc.

Acknowledgments

The authors want to thank the participants and the collaborators for their involvement in the present study. This research have been partially subsidised by the Help to Research Groups (GR15122) of the Junta de Extremadura (Ministry of Economy and Infrastructure); with the contribution of the European Union through FEDER.

REFERENCIAS

Busa, M. A., Jones, S. L., Hamill, J., & van Emmerik, R. E. A. (2016). Multiscale entropy identifies differences in complexity in postural control in women with multiple sclerosis. Gait & Posture, 45, 7-11. https://doi.org/10.1016/j.gaitpost.2015.12.007Busa, M. A., & van Emmerik, R. E. A. (2016). Multiscale entropy: A tool for understanding the complexity of postural control. *Journal of Sport and Health Science, 5(1), 44-51. https://* doi.org/10.1016/j.jshs.2016.01.018.

Costa, M., Goldberger, A. L., & Peng, C.-K. (2002). Multiscale Entropy Analysis of Complex Physiologic Time Series. *Physical Review Letters, 89(6). https://* doi.org/10.1103/PhysRevLett.89.068102.

Dincer, I., & Cengel, Y. A. (2001). Energy, entropy and exergy concepts and their roles in thermal engineering. *Entropy, 3(3), 116–149.*

Ferrari, M., Mottola, L., & Quaresima, V. (2004). Principles, techniques, and limitations of near infrared spectroscopy. *Canadian journal of applied physiology, 29(4), 463–487.*

García-Pallarés, J., & Izquierdo, M. (2011). Strategies to optimize concurrent training of strength and aerobic fitness for rowing and canoeing. *Sports Medicine, 41(4), 329–343.*

Goldberger, A. L., Peng, C.-K., & Lipsitz, L. A. (2002). What is physiologic complexity and how does it change with aging and disease? Neurobiology of aging, 23(1), 23–26.

Gómez-Campos, R., Cossio-Bolaños, M. A., Brousett Minaya, M., & Hochmuller-Fogaca, R. T. (2010). The mechanisms involved in acute fatigue. *Revista Internacional de Medicina y Ciencias de la Actividad Física y del Deporte, 10(40), 537–555.*

Hurd, W. J., Morrow, M. M., & Kaufman, K. R. (2013). Tri-axial accelerometer analysis techniques for evaluating functional use of the extremities. *Journal of Electromyography and Kinesiology, 23(4), 924-929. https://* doi.org/10.1016/j.jelekin.2013.03.010

Kaipust, J. P., Huisinga, J. M., Filipi, M., & Stergiou, N. (2012). Gait variability measures reveal differences between multiple sclerosis patients and healthy controls. *Recuperado a partir de http://digitalcommons.unomaha.edu/biomechanicsarticles/4/*

McGregor, S. J., Armstrong, W. J., Yaggie, J. A., Bollt, E. M., Parshad, R., Bailey, J. J., … Kelly, S. R. (2011). Lower extremity fatigue increases complexity of postural control during a single-legged stance. *Journal of NeuroEngineering and Rehabilitation, 8(1), 43. https://* doi.org/10.1186/1743-0003-8-43

McGregor, S. J., Armstrong, W. J., Yaggie, J. A., Parshad, R. D., & Bollt, E. M. (2011). Fatiguing Exercise Increases Complexity of Postural Control: Control Entropy of High-Resolution Accelerometry. *Medicine & Science in Sports & Exercise, 43(Suppl 1), 526. https://* doi.org/10.1249/01.MSS.0000401451.63095.d3

McGregor, S. J., Busa, M. A., Skufca, J., Yaggie, J. A., & Bollt, E. M. (2009). Control entropy identifies differential changes in complexity of walking and running gait patterns with increasing speed in highly trained runners. *Chaos: An Interdisciplinary Journal of Nonlinear Science, 19(2), 26109. https://* doi.org/10.1063/1.3147423

Meneilly, G. S., Ryan, A. S., Veldhuis, J. D., & Elahi, D. (2011). Increased Disorderliness of Basal Insulin Release, Attenuated Insulin Secretory Burst Mass, and Reduced Ultradian Rhythmicity of Insulin Secretion in Older Individuals1. *The Journal of Clinical Endocrinology & Metabolism. https://* doi.org/10.1210/jcem.82.12.4457

Muyor, J. (2018). Reliability and validity of a new accelerometer (Wimu®) system for measuring velocity during resistance exercises. *Sports Engineering and Technology, Pendiente de Publicación.*

Orellana, J. N., & Torres, B. D. L. C. (2010). La entropía y la irreversibilidad temporal multiescala en el análisis de sistemas complejos en fisiología humana. *Revista Andaluza de Medicina del Deporte, 3(1). Recuperado a partir de http://boletimef.org/biblioteca/2834/articulo/entropia-y-la-irreversibilidad-temporal-multiescala.pdf*

Pareja-Blanco, F., Sánchez-Medina, L., Suárez-Arrones, L., & González-Badillo, J. J. (2016). Effects of Velocity Loss During Resistance Training on Performance in Professional Soccer Players. *International Journal of Sports Physiology and Performance, 1-24.*

https:// doi.org/10.1123/ijspp.2016-0170
Parshad, R. D., McGregor, S. J., Busa, M. A., Skufca, J. D., & Bollt, E. (2012). A statistical approach to the use of control entropy identifies differences in constraints of gait in highly trained versus untrained runners. *Math Biosci Eng, 9(1), 123–45.*
Pincus, S. M. (1991). Approximate entropy as a measure of system complexity. *Proceedings of the National Academy of Sciences, 88(6), 2297–2301*
Pincus, S. M. (2001). Assessing serial irregularity and its implications for health. *Annals of the New York Academy of Sciences, 954(1), 245–267.*
Pincus, S. M., & Huang, W.-M. (1992). Approximate entropy: Statistical properties and applications. *Communications in Statistics - Theory and Methods, 21(11), 3061-3077. https://* doi.org/10.1080/03610929208830963
Richman, J. S., & Moorman, J. R. (2000). Physiological time-series analysis using approximate entropy and sample entropy. *American Journal of Physiology - Heart and Circulatory Physiology, 278(6), H2039-H2049.*
Rodriguez, P. L. (2008). Ejercicio Físico en Salas de Acondicionamiento Muscular. *Madrid: Panamericana. Recuperado a partir de https://books.google.es/books/about/Ejercicio_F%C3%ADsico_en_Salas_de_Acondicion.html?hl=es&id=F36IkFCcf9oC*
Roemmich, R. T., Zeilman, P. R., Vaillancourt, D. E., Okun, M. S., & Hass, C. J. (2013). Gait variability magnitude but not structure is altered in essential tremor. *Journal of Biomechanics, 46(15). https://* doi.org/10.1016/j.jbiomech.2013.07.039
Sánchez-Medina, L., & González-Badillo, J. J. (2011). Velocity Loss as an Indicator of Neuromuscular Fatigue during Resistance Training: Medicine & Science in Sports & Exercise, 43(9), 1725-1734. *https://* doi.org/10.1249/MSS.0b013e318213f880
Sánchez-Medina, L., Pallarés, J., Pérez, C., Morán-Navarro, R., & González-Badillo, J. (2017). Estimation of Relative Load From Bar Velocity in the Full Back Squat Exercise. *Sports Medicine International Open, 1(2), E80-E88. https://* doi.org/10.1055/s-0043-102933
Sanchez-Medina, L., Perez, C. E., & Gonzalez-Badillo, J. J. (2010). Importance of the Propulsive Phase in Strength Assessment. *International Journal of Sports Medicine, 31(2), 123-129. https://* doi.org/10.1055/s-0029-1242815
West, B. J., Rigney, D. R., & Goldberger, A. L. (1990). Caos y fractales en la fisiología humana. *Investigación y ciencia, (163), 30-38.*
Wilmore, J. H., & Costill, D. L. (2007). Fisiología del esfuerzo y del deporte. *Editorial Paidotribo.*