Silva, L., Vaz, J. R., Castro, M. A., Serranho, P., Cabri, J. M. H., Pezarat-Correia, P. (2015). Recurrence quantification analysis and support vector machines for golf handicap and low back pain EMG classification. *Journal of Electromyography & Kinesiology, 25*, 637-647.

Recurrence Quantification Analysis and Support Vector Machines for Golf Handicap and Low Back Pain EMG classification.

Silva, Luís; Faculdade de Motricidade Humana, Universidade de Lisboa
Vaz, João Rocha; Faculdade de Motricidade Humana, Universidade de Lisboa
Castro, Maria António; Coimbra College of Health Technology, Polytechnic Institute of Coimbra
Serranho, Pedro; Departamento de Ciências e Tecnologia, Universidade Aberta
Cabri, Jan; Norwegian School of Sport Sciences
Pezarat-Correia, Pedro; Faculty of Human Kinetics, Technical University of Lisbon

Abstract

The quantification of non-linear characteristics of electromyography (EMG) must contain information allowing to discriminate neuromuscular strategies during dynamic skills. In golf, both handicap (Hc) and low back pain (LBP) are main factors associated with the occurrence of injuries. The aim of this study was to analyze the accuracy of support vector machines SVM on EMG-based classification to discriminate Hc (low and high handicap) and LBP prevalence (with and without LPB) in the main phases of golf swing. For this purpose recurrence quantification analysis (RQA) features of the trunk and the lower limb muscles were used to feed a SVM classifier. Recurrence rate (RR) and the ratio between determinism (DET) and RR showed a high discriminant weight. The Hc classifications accuracy for the swing, backswing (BS), and downswing (DS) were 94.4±2.7%, 97.1±2.3%, and 95.3±2.6%, respectively. For LBP, the accuracy was 96.9±3.8% in the swing, and 99.7%±0.4% in BS. External oblique (EO), biceps femoris (BF), semitendinosus (ST) and rectus femoris (RF) showed high accuracy depending on the laterality within the phase. RQA features and SVM showed a high capacity in discriminating muscles within swing phases by Hc and by LBP. Low back pain golfers showed less neuromuscular coordination strategies than asymptomatic.

Keywords: SVM, RQA, Golf, neuromuscular discrimination, patterns recognition

3.1. Introduction

Electromyography (EMG) is widely used for neuromuscular pattern characterization. Researchers who use EMG in the time domain usually choose variables related to intensity, duration, and muscle activation sequence. The main problem of surface EMG, when applied to motor behavior studies, is its quantification according to the description of the physiologic phenomenon. For this purpose, as a time series the EMG signal requires methods that are able to detect the nonlinear characteristics, for instance, the stochastic, non-stationary and deterministic behavior (Lei and Meng 2012). Thus, multivariate and non-linear methods are needed, rather than linear approaches that are often not appropriate (Marwan et al, 2002; Tolambiya et al. 2011).

Recurrence plots (RP) were introduced by Eckmann et al.(1987), who described a graphical tool for measuring the time consistency of a dynamic system. Quantification based on RP, Recurrence Quantification Analysis (RQA), was developed later by Webber and Zbilut (1994) and is regarded as a useful method of nonlinear data analysis. Dynamic systems are explained by the time evolution of the phase space trajectory. The vector $\vec{x}(t)$ in a d-dimensional space, formed by the d variables $x_1(t), x_2(t), \ldots, x_d(t)$ about the state of a system in time, is called phase space. This vector is specified by its velocity vector $\dot{\vec{x}}(t)$ as it is moving in time and in a certain direction. (Marwan et al. 2007).

The application of RQA on EMG has proven to be a sensitive tool to study muscle fatigue, showing high sensitivity to changes in muscle status like motor unit synchronization when compared with the traditional spectral analysis. It is highly correlated with spectral variables in the biceps brachii (Farina et al. 2002; Filligoi and Felici 1999), the extensor carpi radialis (Del Santo et al., 2006), and the back muscles (Ikegawa et al., 2000). These afore mentioned studies suggested that an increase in the percentage of determinist (%DET) is related with an increase in fatigue. Not only the %DET, but also the percentage of recurrence (%RR), is influenced by the degree of synchronization and conduction velocity (Farina et al., 2002).

Support Vector Machines (SVM) are complex and advanced algorithms in the field of supervised learning (Boser et al., 1992; Vapnik 1999), used in classification and regression problems. SVM showed a high accuracy on EMG-based features when compared with others classifiers of myoelectric control (Castellini and Smagt 2009), neuromuscular disorders (Güler and Koçer 2005), and kinesiologic analysis (Shi et al. 2009). In addition to the classification, SVM have also showed high ability in the regression of kinetic parameters using EMG in grasping postures (Castellini et al. 2009) and in isometric wrist flexion and extension (Ziai and Menon, 2011). Sultornsanee et al. (2011) applied both RQA features and SVM to distinguish neuromuscular disorders in three groups, i.e. healthy, myopathy, and neuropathy, reaching an accuracy between 93.33% and 100%.

The golf swing is a dynamic complex task requiring both power and accuracy (Hume et al., 2005). The two main factors associated with changes in the golf swing are the handicap (Hc) and the incidence of low back pain (LBP) (Cabri et al, 2009; Lindsay et al, 2000). Lindsay et al (2000) stated that more than 70% of golf players experienced injuries resulting in playing at an unsatisfactory skill level during a short period of time. LBP has been implicated as the major complaint of golfers as well as the body region associated with a larger incidence of injuries (Cabri et al., 2009; Lindsay et al., 2002; McHardy et al., 2007). This led to a growing interest in quantifying the factors that can be influenced by LBP (Gluck et al., 2008; Vad, 2004), as the e.g. EMG onset (Cole and Grimshaw 2008a; Horton et al., 2001).

The aim of this study was to identify the accuracy of SVM on EMG-based classification to discriminate Hc (low and high handicap) and LBP (with and without LPB) in the main phases of golf swing: preparation (backswing), execution (downswing) and reestablishment (follow-through). Additionally, we intended to determine 1) which muscles have discriminatory power and 2) which of the RQA features are the most relevant.

3.2. Method

3.2.1. Subjects

Twenty-one golfers performed eight trials with two clubs (pitch, 7-iron). The subjects were divided by Hc and by LBP perception after conducting an 18-hole golf course (Table 1). Twelve subjects (age = 52.5±12.13 years; Hc = 15.12±12) were assigned to two groups: with (five golfers) and without (seven golfers) LBP. Age ($U = 9.0$; $p = 0.189$), handicap ($U = 15.5; p = 0.785$), expertise time ($U = 9.0; p = 0.246$), body mass ($U = 9.0; p = 0.699$), and height ($U = 9.0; p = 0.909$) were homogeneous between LBP groups. Ten subjects were assigned in two others group: five with low handicap (LHc) $Hc < 5$ (0.7 ± 2.2) and six with high handicap (HHc) ($Hc \geq 18$ (24.3 ± 4.6). Hc was based on the European Golf Association recommendations (EGA, 2012). For the LBP discrimination the Musculoskeletal Injury Questionnaire for Senior Golfers (Fox, Lindsay, & Vandervoort, 2002) was used, namely the percentage means how often golfers are aware of LBP after golfing 18 holes. Participants selected in the no LBP (NLBP) group answered “0%” and not reported any musculoskeletal injury diagnosis with LBP. Participants with more than 65% of LBP were enlisted in the LBP group.

Tabela 1 [Table 1 – Participants characteristics]

	Groups	Mínimum	Máximum	Mean	Standard Deviation
Age (years)	NLBP	27.0	63.0	48.1	11.7
	LBP	40.0	69.0	58.6	10.9
	LHc	21.0	37.0	30.4	7.0
	HHc	35.0	62.0	44.0	10.9
Mass (kg)	NLBP	68.0	90.0	82.5	8.9
	LBP	74.0	90.5	80.7	6.6
	LHc	67.0	79.0	70.6	4.9
	HHc	56.0	108.0	80.6	19.4
Height (m)	NLBP	1.68	1.80	1.75	0.05
	LBP	1.69	1.81	1.75	0.05
	LHc	1.68	1.82	1.72	0.06
	HHc	1.60	1.83	1.72	0.08
Handicap (Hc)	NLBP	8.0	22.0	14.5	4.4
	LBP	8.40	28.5	16.0	7.5
	LHc	-1.0	4.5	0.7	2.2
	HHc	18.0	29.0	24.3	4.6
Experience (years)	NLBP	4.0	12.0	7.0	2.8
	LBP	2.25	30.0	12.5	10.36
	LHc	12.0	22.0	19.2	4.4
	HHc	2.0	15.1	5.9	5.3

NLBP – no low back pain; LBP – low back pain; LHC – low back pain; HHC – high handicap.

3.2.2. EMG procedures

EMG data was collected with bioPLUX® research 2010 telemetric equipment (Plux, Lisbon, Portugal) using active surface electrodes (Al/AgCl, disk shape 10 mm of diameter) and surfaces of detection AMBU® BlueSensor N (shape 30 x 22 AMBU, Ballerup, Denmark). The EMG signals were collected with sampling frequency of 1000Hz, filtered with a bandpass filter between 10 and 500 Hz, common-mode rejection ratio (CMRR) of 110 dB and input impedance was greater than 100 MΩ. After storage, the data were digitally filtered (10–490 Hz).

The skin was prepared by hair removal, abrasion and alcohol cleaning and muscle contraction was performed before fixation in order to better visualize the muscle belly. The electrodes were placed with a 20 mm center-to-center distance and applied in parallel to the muscle fibers, bilaterally on *rectus femoris* (RF); *biceps femoris* (BF); *semitendinosus* (ST); *external oblique* (EO); and unilaterally on the left *gluteus* *maximus* (GM); *erector spinae* (ES), as described by (Hermens et al., 1996). The ground electrode was placed on the manubrium.

3.2.3. Video data recording, processing and kinematic analysis

Three high-speed Basler A602fc cameras (Basler Vision Technologies, Ahrensburg, Germany) at 100 Hz were placed in anterior, posterior and superior oblique positions to determine the swing phases. A fourth Casio Ex-FH20 camera (Casio, Tokyo, Japan) at 1000 Hz was placed in front of the ball, in order to determine the instant of impact.

Two reflective tapes were placed on the club to divide the swing in three phases (Hume et al., 2005): (1) the Backswing – from the beginning until the top of the swing; (2) the Downswing – from the top until impact; and (3) the Follow-Through – from impact until the end of the swing. SIMI 3D Motion system (SIMI Reality Motion System GmbH, Unterschleissheim, Germany) was used for EMG-synchronized 3D kinematic analysis.

3.2.4. Recurrence Quantification Analysis

RP is a mathematical technique that allows visualizing the recurrence of dynamical systems. A set of vector $\{\vec{x_i}\}_{i=1}^{N}$ of a system, is described by a series that represents a trajectory in the phase space. RP depends on the matrix:

$$R_{i,j} = \begin{cases} 1: \vec{x}_i \approx \vec{x}_j \\ 0: \vec{x}_i \not\approx \vec{x}_j \end{cases} \quad i,j = 1 \ldots, N \quad (1)$$

So, RP for time-discrete variables, where $t = i\Delta t$, is defined as

$$R_{i,j} = \Theta(\varepsilon_i - \|\vec{x}_i - \vec{x}_j\|) \qquad (2)$$

where ε_i is the cut-off distance, $\|\cdot\|$ is a given norm, and $\Theta(x)$ the Heaviside function. For this study the Euclidian norm was used as Neighborhood method with a threshold $\varepsilon_i = 10\%$ of the mean phase space (Marwan et al. 2007) The phase space reconstruction requires two main parameters, embedding dimension (m) and time delay (τ). The τ value was found by *Mutual information* ($\tau = 2$), and then m value adjusted by false nearest neighbors, than a vector in phase space is reconstructed by (Marwan et al., 2007);

$$\vec{x}_i = \sum_{k=0}^{m-1} \xi_{i+k\tau} + \vec{e}_k \qquad (3)$$

RQA features were extracted with Toolbox 5.17 (R28.20; PIK Potsdam). Given a *N* number of points on the phase space trajectory, N_l is the number of diagonal lines in the recurrence plot, N_v the number of vertical lines in the recurrence plot, and *P(l) and P(v)* are the histogram of the line lengths of diagonal and vertical lines, respectively. So, the features extracted are (Marwan et al., 2007)

Recurrence rate (RR), a measure based on recurrence density that depends on the average number of neighbors of each point on the trajectory:

$$RR = \frac{1}{N^2} \sum_{i,j=1}^{N} R_{i,j} \qquad (4)$$

Determinism(DET) is based on diagonal lines, depends on the histogram $P(\varepsilon, l)$ and corresponds to the ratio of recurrence points that form diagonal lines in relation to all recurrence points:

$$DET = \sum_{l=l_{min}}^{N} lP(l) / \sum_{i,j}^{N} R_{i,j} \qquad (5)$$

Divergence (DIV) is the inverse of L_{max}, another measure based on diagonal lines:

$$DIV = \frac{1}{L_{max}} \quad (6)$$

where L_{max} is the length of the longest diagonal line $L_{max} = \max(\{l_i; i = 1, \dots N_l\})$, and $N_l = \sum_l \geq l_{min}\ P(l)$ is the total number of diagonal lines.

Entropy (ENT) is based on diagonal lines and it means the Shannon entropy of the probability $p(l) = P(l)/N_l$ to find a diagonal line of exactly length l in the recurrence plot.

$$ENT = -\sum_{l=l_{min}}^{N} p(l) \ln p(l) \qquad (7)$$

Laminarity (LAM) is based on vertical lines, corresponds to the ratio between the vertical structures recurrence points and the all set of recurrence points computed.

$$LAM = \sum_{v=v_{min}}^{N} vP(v) / \sum_{l=1}^{N} vP(v) \quad (8)$$

Trapping Time (TT) is the average length of the vertical lines:

$$TT = \frac{\sum_{v=v_{min}}^{N} v(P(v)}{\sum_{v=v_{min}}^{N} P(v)} \quad (9)$$

The ratio between DET and RR (DET/RR), and between *laminarity* and *determinism* (LAM/DET) was also considered to verify the utility of the relationship between recurrence, vertical and diagonal lines.

3.2.5. Support Vector Machines

Support vector machines are a useful machine learning tool developed in the 90's (Boser et al., 1992; Cortes and Vapnik 1995) for solving classification problems. Given a training set of inputs x_i and the output label y_i, where $x_i \in \mathbb{R}^n$ and $y \in \{-1,1\}$, the support vector machines search the solution of the following optimization problem (see Burges, 1998; Hsu et al., 2003-2010):

$$\min_{w,b,\xi} \quad \frac{1}{2} w^T w + C \sum_{i=1}^{l} \xi_i \qquad (10)$$

subject to

$$y_i(w^T \phi(x_i) + b) \geq 1 - \xi_i \quad (11)$$

$$\xi_i \geq 0$$

The training vectors x_i were mapped into a higher dimensional space with the kernel radial basis function (RBF) expressed as follows:

$$K(x_i, y_i) = \exp\left(-\gamma \left\| x_i - x_j \right\|^2\right), \gamma > 0 \quad \text{(eq. 12)}$$

The grid search was performed with $C = 2^{-5:2:17}$ and $\gamma = 2^{-9:2:5}$ based on previous recommendations (Hsu et al., 2010). In both analysis, Hc and LBP, the trails were separated in two parts, 80% for training and the others 20% for test. High discriminatory power was considered for muscles (alone) with an accuracy equal or higher than 85%.

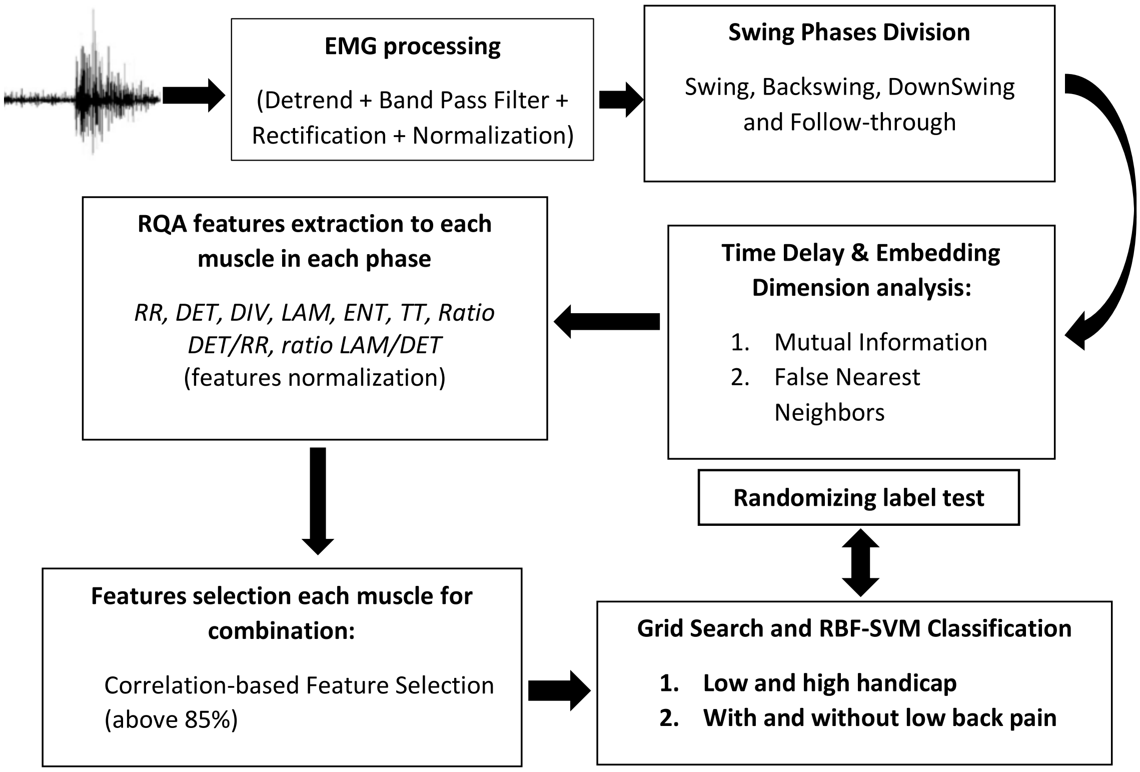


*Figura 1 [**Fig. 1.** Flow chart research procedures].*
Hc – handicap; LBP – Low back pain; RR – recurrence rate; DET – determinism; DIV – divergence; ENT – entropy; LAM – Laminarity; TT – trapping time.

3.2.6. Complementary statistical analysis

Four normalization steps were performed: Amplitude; Z-score for RQA analysis; time scale by the minimum phase duration; features that feed the SVM classifier.

The Mann-Whitney U test was performed to control the homogeneity between LPB and NLBP. Friedman test and respective multiple comparisons were performed for RR during swing and BS, each group alone ($\alpha = 5\%$).

Features were selected using the Correlation-based Feature Selection algorithm (CBFS) (Hall, 1999; Zhao et al., 2010).

Data processing was performed with MATLAB® R2013a (Mathworks Inc., Natick Massachusetts, USA). Figure 1 summarizes the data procedures in this study.

3.3. Results

CBFS features selection for both Hc and LBP (Figure 2) were DET/RR, RR, and DIV. The DET/RR ratio were selected 72.5% and 60% times, the RR 60% and 55%, and DIV in 37.5% and 45%, Hc and LBP, respectively. However, DIV showed no relevance on BS when it was used to discriminate trials of LBP and NLBP.

Tables 2 - 5 show the accuracy and percentage of support vectors used for each muscle individually for each swing phase and for the entire swing. The BS was the major discriminant phase. FT showed no discriminatory capacity in any of the situations studied, and DS did not show enough capability to classify LBP (considering accuracy ≥ 85%). Figure 3 shows the grid search for two channels, four and five channels. Figures 4 and 5 show features sets with the channels with higher accuracy by phase, for Hc and LBP, respectively. The classification accuracy for Hc was 94.4±2.7 [91.6-98.1%] during the swing, 97.1±2.3 [94.9-99.1%] in the BS, 95.3±2.6 [91.6-97.2%] during the DS. During BS, the right EO showed the greatest accuracy (94.9%), followed by right BF (94.4%), left ST (88.9%), right ST (86.9%), and right RF (86.9%). For LBP, the results were 96.9±3.8 [90.9-100%] for the swing, and 99.7%±0.4 [99.3-100%] in the BS. The left BF showed the higher accuracy (99.3%) followed by the left ST (88.7%), right BF (86.6%), and left RF (85.9%).

The RR showed significant differences between muscles for both, the swing $(NLBP: \chi_F^2(9) = 306.48, p < 1\%; LBP: \chi_F^2(9) = 350.32, p < 1\%)$, and the BS $(NLBP: \chi_F^2(9) = 496.22, p < 1\%; LBP: \chi_F^2(9) = 335.49, p < 1\%)$. Figure 5 shows the multiple comparison

Tabela 2 [Table 2 – Individual left muscle RQA and SVM parameters by handicap]

	Serie (n=132)	Selected Features	7-iron & Pitch		
			$C-\gamma$	%VS	ACC
RF	Swing	RR, DIV, TT	2^7-2	23.4	**91.6**
	BS	RR, DIV, DET/RR	$2-2^{-3}$	72.9	**86.9**
	DS	RR, DET, DIV, ENT, LAM, TT, DET/RR, LAM/DET	2^3-2	42.1	**87.9**
	FT	RR, DIV	$2^{13}-2^{-1}$	63.6	65.4
OE	Swing	RR, ENT, DET/RR	$2-2^{-1}$	61.7	**85.1**
	BS	RR, LAM, DET/RR	$2^{13}-2^3$	44.9	80.4
	DS	RR	$2^{-1}-2^5$	86.9	64.5
	FT	DET, ENT, LAM, TT	2^7-2^5	86.0	59.8
BF	Swing	RR, ENT, DET/RR	2^9-2^{-1}	49.5	77.6
	BS	DIV, DET/RR	2^7-2^{-1}	34.6	84.1
	DS	RR, DET/RR	2^3-2^{-1}	51.4	**85.0**
	FT	DET	$2-2^{-7}$	88.8	65.42
ST	Swing	RR, DET, LAM	2^3-2	43.9	81.1
	BS	RR, DET/RR	2^9-2	34.6	**88.8**
	DS	RR, ENT, TT, DET/RR	$2-2$	38.3	**91.6**
	FT	RR, ENT, TT, DET/RR	$2^{-1}-2^3$	88.7	80.4
GM	Swing	RR, ENT, TT	$2^{11}-2$	43.0	84.1
	BS	DET, DIV, LAM, TT, DET/RR, LAM/DET	2^3-2	57.9	80.4
	DS	DET/RR	$2^{13}-2^{-1}$	54.2	78.5
	FT	RR, ENT, DET/RR	2^3-2^{-1}	61.7	83.2
ES	Swing	DET, DIV, LAM, TT, LAM/DET	2^3-2	48.6	83.2
	BS	RR, LAM, DET/RR	2^9-2^5	59.8	77.6
	DS	DIV, DET/RR	2^9-2	55.1	75.7
	FT	DET/RR	2^5-2^3	87.9	60.0

Legend: RF – Rectus femoris; EO – external oblique; BF – Biceps femoris; ST – Semitendinous; GM – Gluteus maximus; ES – Erector Spinae; BS – Backswing; DS – Downswing; FT – Follow-Through. Bold – Equal or Higher than 85%.

Tabela 3 [Table 3 – Individual right muscle RQA and SVM parameters by handicap]

Serie (n=132)		Selected Features	7-iron & Pitch		
			$C-\gamma$	%VS	ACC
RF	Swing	DIV, LAM, DET/RR	$2^{13}-2^{3}$	31.0	78.2
	BS	DET/RR	$2^{-1}-2^{-5}$	53.5	66.7
	DS	RR, DET/RR	$2^{7}-2^{-1}$	27.5	79.5
	FT	DIV, LAM, DET/RR, LAM/DET	$2^{5}-2$	54.9	73.1
OE	Swing	RR, DIV, DET/RR	$2^{5}-2$	33.1	82.1
	BS	ENT, LAM/DET	$2^{11}-2$	14.1	**94.9**
	DS	DET, LAM, DET/RR, LAM/DET	$2^{7}-2$	20.4	**85.9**
	FT	ENT, DET/RR	$2^{11}-2$	39.7	80.7
BF	Swing	RR, DIV, TT	$2^{3}-2^{-1}$	57.0	**86.0**
	BS	DIV, TT, DET/RR	$2^{-1}-2^{-1}$	52.3	**94.4**
	DS	TT, DET/RR, LAM/DET	$2^{-3}-2$	87.9	82.2
	FT	RR, DET/RR, LAM/DET	$2^{-3}-2$	94.4	70.1
ST	Swing	RR, DIV, LAM, DET/RR, LAM/DET	$2^{3}-2^{3}$	57.9	80.4
	BS	RR, LAM, TT, LAM/DET	$2^{13}-2^{3}$	36.5	**86.9**
	DS	RR, DIV, TT, DET/RR, LAM/DET	$2^{13}-2^{3}$	39.3	82.2
	FT	DET, ENT, TT, DET/RR, LAM/DET	$2^{-1}-2^{-1}$	86.9	74.8

Legend: RF – Rectus femoris; EO – external oblique; BF – Biceps femoris; ST – Semitendinous; GM – Gluteus maximus; ES – Erector Spinae; BS – Backswing; DS – Downswing; FT – Follow-Through. Bold – Higher than 85%.

Tabela 4 [Table 4 – Individual left muscle RQA and SVM parameters by low back pain]

	Phase (n=176)	RQA Selected Features	SVM results		
			$C-\gamma$	%VS	ACC
RF	Swing	RR, DIV, TT, DET/RR	$2^{13}-2$	33.1	**87.3**
	BS	LAM, DET/RR	$2-2^{-1}$	51.4	**85.9**
	DS	RR, DET, DIV, ENT, LAM/DET	$2^{7}-2^{3}$	52.1	77.5
	FT	LAM, DET/RR	$2-2^{3}$	73.9	62.0
OE	Swing	RR, ENT, TT	$2^{5}-2^{-1}$	63.4	68.3
	BS	RR, DET/RR	$2^{8}-2$	45.8	82.4
	DS	RR, DET, DIV	$2^{5}-2$	76.7	70.4
	FT	RR, DET, ENT, LAM, TT	$2^{-5}-2^{-5}$	82.4	63.4
BF	Swing	RR, DET, DIV, LAM, DET/RR, LAM/DET	$2^{7}-2$	38.7	83.1
	BS	RR, DET/RR	$2^{-3}-2^{-1}$	42.3	**99.3**
	DS	DIV, ENT, LAM, TT, LAM/DET	$2^{5}-2^{3}$	49.3	84.5*
	FT	RR, DET, ENT, LAM, TT, DET/RR, LAM/DET	$2^{15}-2^{3}$	49.3	74.6
ST	Swing	RR, DIV, ENT, TT, DET/RR	$2^{9}-2$	26.8	**90.9**
	BS	RR, DET, LAM, TT	$2-2^{-3}$	83.8	**88.7**
	DS	ENT, LAM/DET	$2^{13}-2^{-1}$	62.7	66.2
	FT	DET, ENT, TT, DET/RR	$2^{-1}-2$	89.4	62.0
GM	Swing	ENT, DET/RR, LAM/DET	$2^{7}-2$	34.5	**88.0**
	BS	ENT, DET/RR	$2^{3}-2^{-1}$	50.7	78.9
	DS	DIV, ENT, LAM, DET/RR, LAM/DET	$2^{11}-2$	42.3	77.5
	FT	DET, DIV, ENT, LAM, TT, DET/RR, LAM/DET	$2^{5}-2^{3}$	43.7	79.6
ES	Swing	RR, DET, ENT, LAM/DET	$2^{3}-2^{-1}$	43.7	**85.2**
	BS	RR, DET, LAM, DET/RR, LAM/DET	$2^{5}-2$	52.8	76.1
	DS	DIV, LAM	$2^{-1}-2^{-1}$	69.0	75.4
	FT	RR, DIV, DET/RR	$2^{15}-2$	52.1	73.9

Legend: RF – Rectus femoris; EO – external oblique; BF – Biceps femoris; ST – Semitendinous; GM – Gluteus maximus; ES – Erector Spinae; BS – Backswing; DS – Downswing; FT – Follow-Through. Bold – Higher than 85%.

Tabela 5 [Table 5 – Individual right muscle RQA and SVM parameters by low back pain]

Serie (n=176)		Selected Features	SVM results		
			$C-\gamma$	%VS	ACC
RF	Swing	RR, DIV, LAM, LAM/DET	$2^8 - 2^{-1}$	67.6	77.5
	BS	ENT, LAM, DET/RR	$2 - 2$	66.9	72.5
	DS	DET, DIV, ENT, LAM/DET	$2^3 - 2$	74.7	72.5
	FT	DET, DIV, DET/RR, LAM/DET	$2 - 2$	78.9	74.0
OE	Swing	RR, TT, DET/RR	$2^{15} - 2^{-1}$	38.7	73.2
	BS	DET/RR, LAM/DET	$2^{15} - 2$	42.3	79.6
	DS	RR, DIV	$2^{-3} - 2^{-3}$	100	63.4
	FT	RR	$2^5 - 2^3$	90.1	62.7
BF	Swing	DET, DIV, LAM, TT, DET/RR	$2^9 - 2$	42.3	81.0
	BS	RR, DET, LAM, TT, DET/RR	$2^3 - 2$	46.5	**86.0**
	DS	RR, DIV	$2^{-5} - 2^{-9}$	100	57.0
	FT	DIV, DET/RR	$2^3 - 2^5$	94.4	72.5
ST	Swing	RR, DET, DIV	$2^{13} - 2$	29.6	**86.6**
	BS	TT, DET/RR, LAM/DET	$2^9 - 2$	45.1	78.2
	DS	RR, ENT, LAM, TT	$2^9 - 2$	56.6	72.5
	FT	DET/RR	$2^{-1} - 2$	55.6	64.1

Legend: RF – Rectus femoris; EO – external oblique; BF – Biceps femoris; ST – Semitendinous; GM – Gluteus maximus; ES – Erector Spinae; BS – Backswing; DS – Downswing; FT – Follow-Through. Bold – Higher than 85%.

3.4. Discussion

This study intended to identify the quantitative power accuracy from RQA features to classify Hc and LBP, using SVM as classifier, in critical phases of golf swing. Analyzing the discriminatory power between muscles due to several constrains gives information about neural coordination.

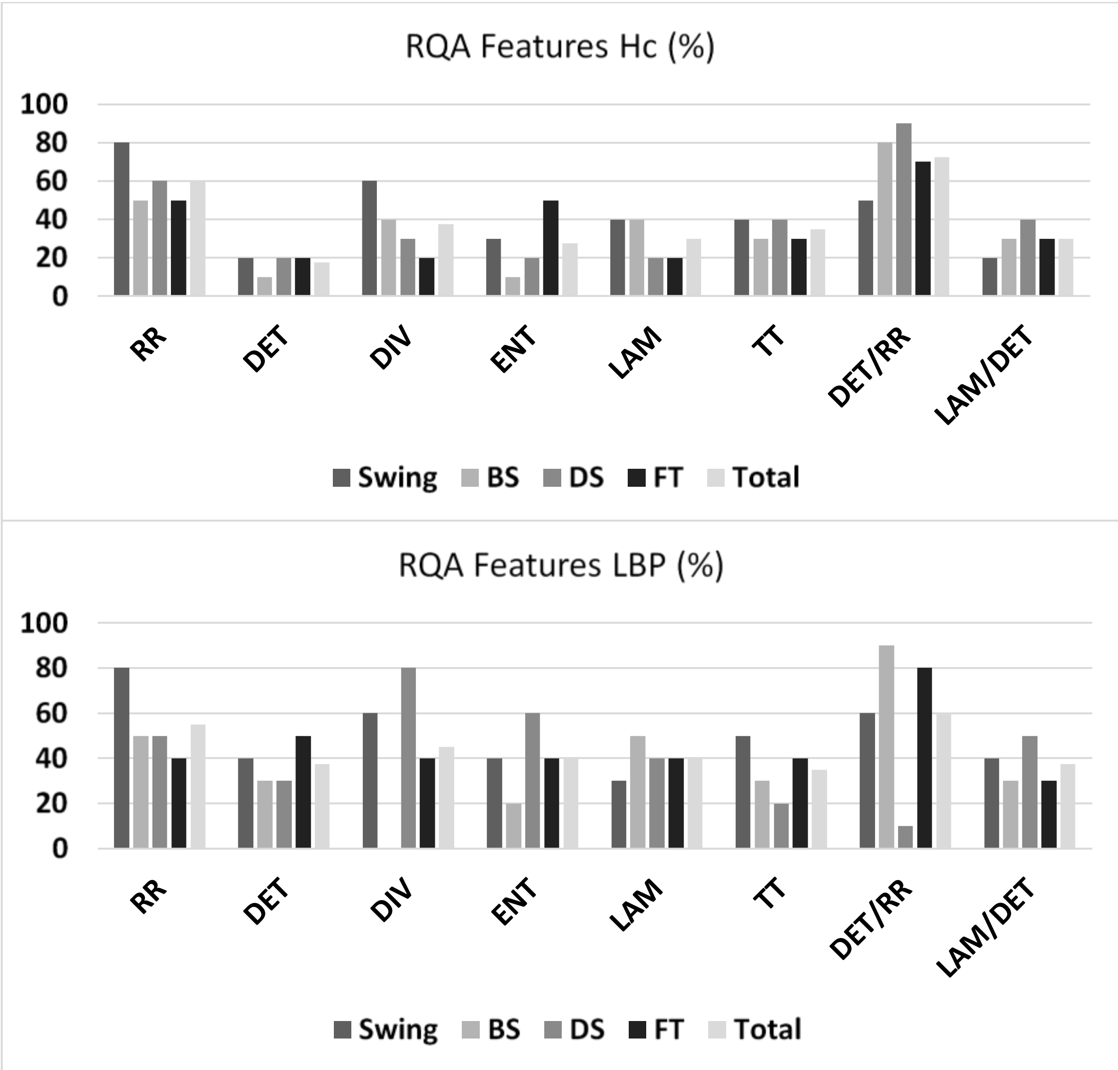


Figura 2 [Fig. 2. Correlation-based Feature Selection for Hc and LBP]

Hc – handicap; LBP – Low back pain; RR – recurrence rate; DET – determinism; DIV – divergence; ENT – entropy; LAM – Laminarity; TT – trapping time; BS – backswing; DS – downswing; FT – follow-through.

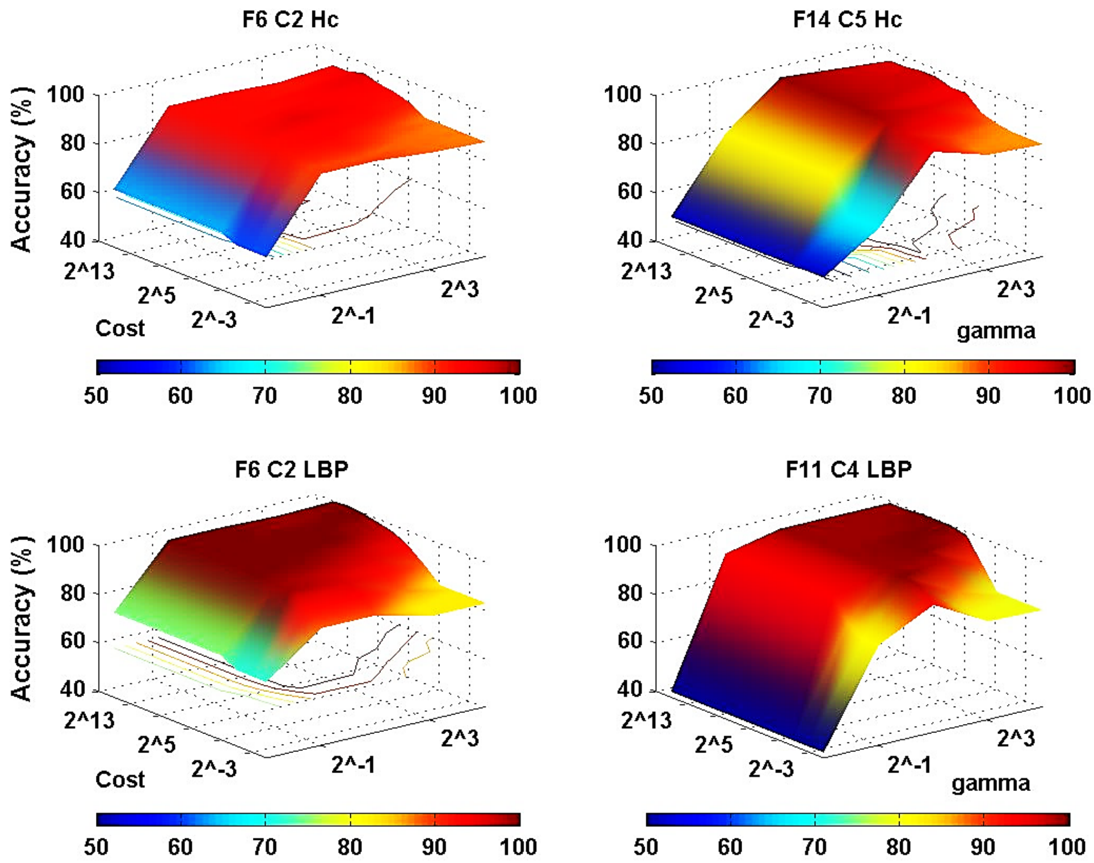


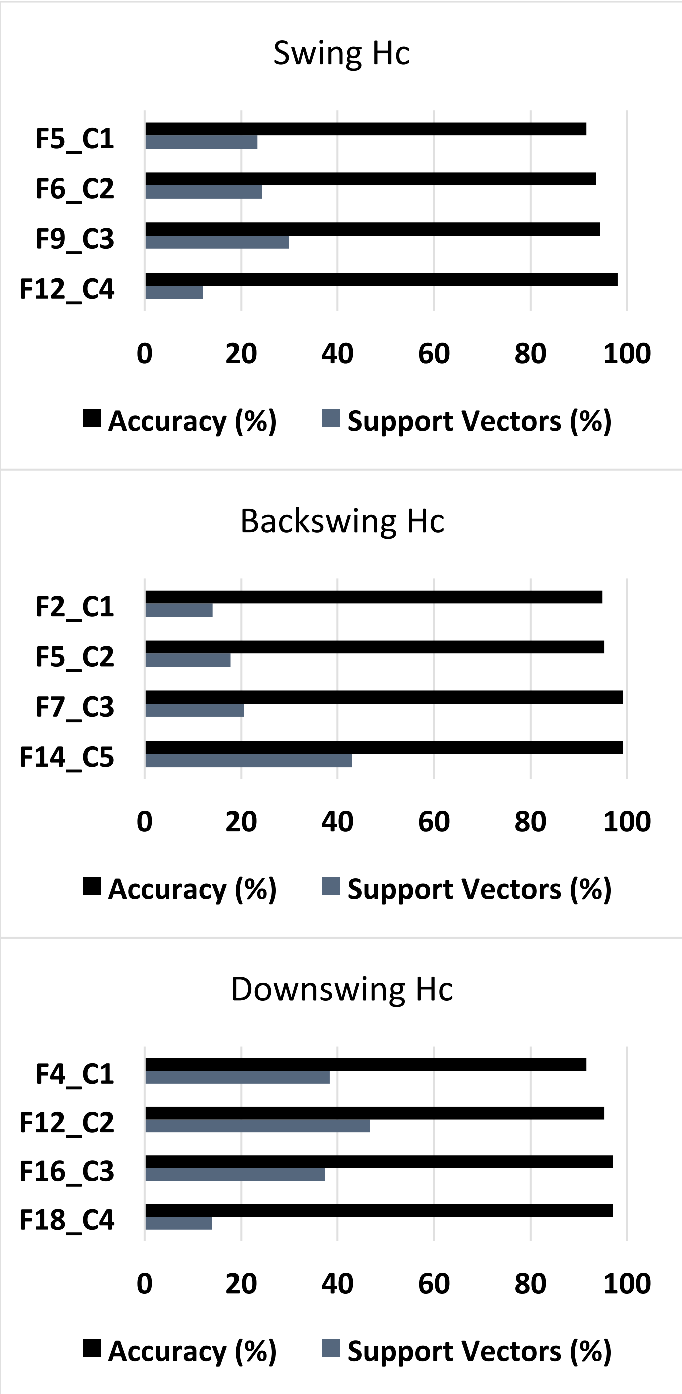
*Figura 3 [**Fig. 3.** Grid Search for different number of features and channels by Hc and LBP]*

Hc – handicap; LBP – Low back pain; F number– number of features; C number – number of channels.

3.4.1. Features selection

Features are vectors that contain information, which enables a (better or worse) classification. Therefore, it is a critical aspect. The RP visualization of the rectified EMG signal for each phase is similar to a mixture between drift and disrupted non-stationary state. Two issues related to dimensionality must be present: (1) the features with better representation for each muscle (features dimensionality) (2) the muscles that best discriminate each phase (channels).

The increase of accuracy when the number of channels was equal or greater than three are similarly to literature (Tavakolan et al., 2011), besides different purposes of classification. The use of 4 channels seems suitable to classification problems based on EMG. In the present study, the LBP group achieved 100% with two and four channels during the BS. Sultornsanee et al (2011) also found accuracies of 100% with RQA features but only using RR, DET and LAM to classify neuromuscular disorders. It is believed that the classification of neuromuscular disorders may be easier due the myogenic and neurogenic differences. The myogenic have less membrane potentials due to atrophy (short-lasting and high amplitude record), and neurogenic due to the loss of axons (long-lasting and high-amplitude record) (Dobrowolski et al., 2012).



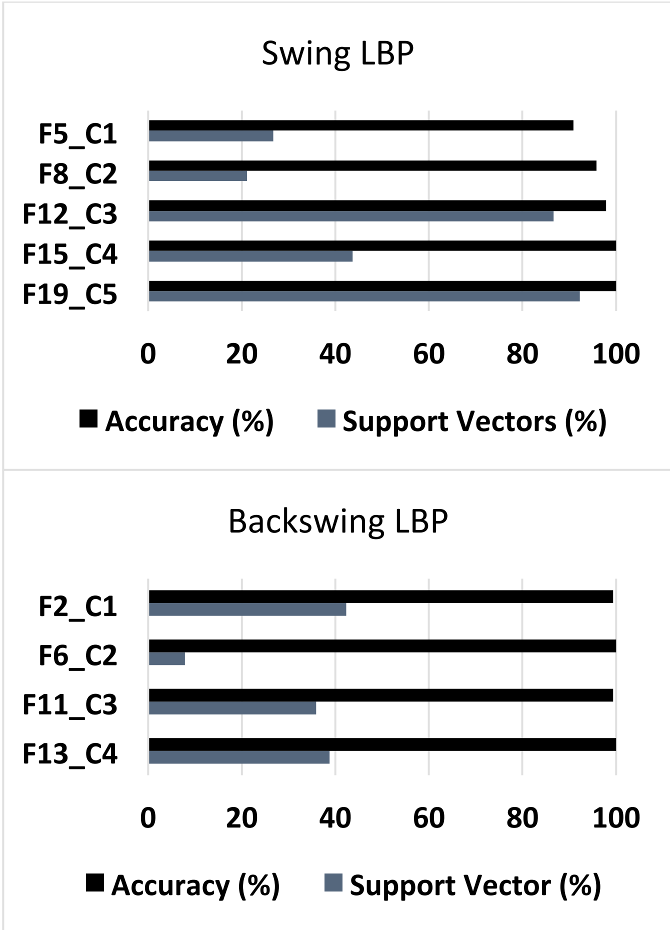


*Figura 4 [**Fig. 4.** Hc and LBP Discriminatory Features and channels set by relevant phase (features above 85% alone)].*

Hc – handicap; LBP – Low back pain; F number – number of features; C number – number of channels.

LBP discrimination had the LAM in 50% of the models. The DET did not show an elevated contribution when used alone. On the other hand, the DET/RR had a mean value of 66.3%, achieving 90% of the SVM models, namely in DS for Hc and BS for LBP. The DET has been showing good results in studies about motor units synchronization and changes determined by fast transitions of force production (Farina et al., 2002; Filligoi and Felici, 1999). The set of features with RR, DET, DIV means that recurrence density and the information based on diagonal lines are the most important to discriminate Hc and LBP muscle activity. In trails with periodic-chaos/chaos-periodic transitions the measures based on diagonal structures increase when vertical measures shows highly drop (Marwan et al., 2007).

3.4.2. Handicap

The major handicap discriminatory muscles during all swing were the RF, OE and GM from left side, and the right BF. The total swing is composed by a number of different motor actions for the same muscle. Accordingly, the ability of the muscles to discriminate the Hc group when performing various motor actions in same task gives information about different strategies due the skill level. Those muscles contain several EMG information relating muscle and load torques, force-velocity, and force-length relationships (Enoka, 1996) during the swing.

The top of the BS could be the primary position that justifies these results, since there is an elastic energy transferring to downswing and then maximizing the impact on the ball. An increase in ground reaction force will occur in the trail foot (right foot in right handed golfers) during the BS, followed by a transferring of weight to the lead foot (left foot in right handed golfers) during the DS phase (Hume et al., 2005). In the top of BS, the ground reaction force achieves mean values of 64.5% of body weight in the trail foot and 29% in the lead foot (Chu et al., 2010). The left OE is axial rotator of the trunk to the right during the BS, stretching the hip and the trunk muscles, which corresponds to an increase of the angle between the pelvis and upper torso segments referred to as X- factor (Cheetham et al., 2001). Increasing the X-Factor at top of backswing should facilitate a high club head speed at impact. However, the reason behind the power of discrimination of these muscles for all swing could be also related with the activity during the early DS. The X-Factor in the top of BS and the maximum that occurs at the early stage of DS ("X-Factor Stretch") is 11% higher in highly skilled golfers than the less-skilled (Cheetham et al., 2001). This means that in LHc golfer's the pelvis turns back towards the ball while the right shoulder continues to rotate to the right. So, during the DS, the left EO activity increases (Ashish et al., 2008), remaining high close to the impact (Ashish et al., 2008; Silva et al., 2013).

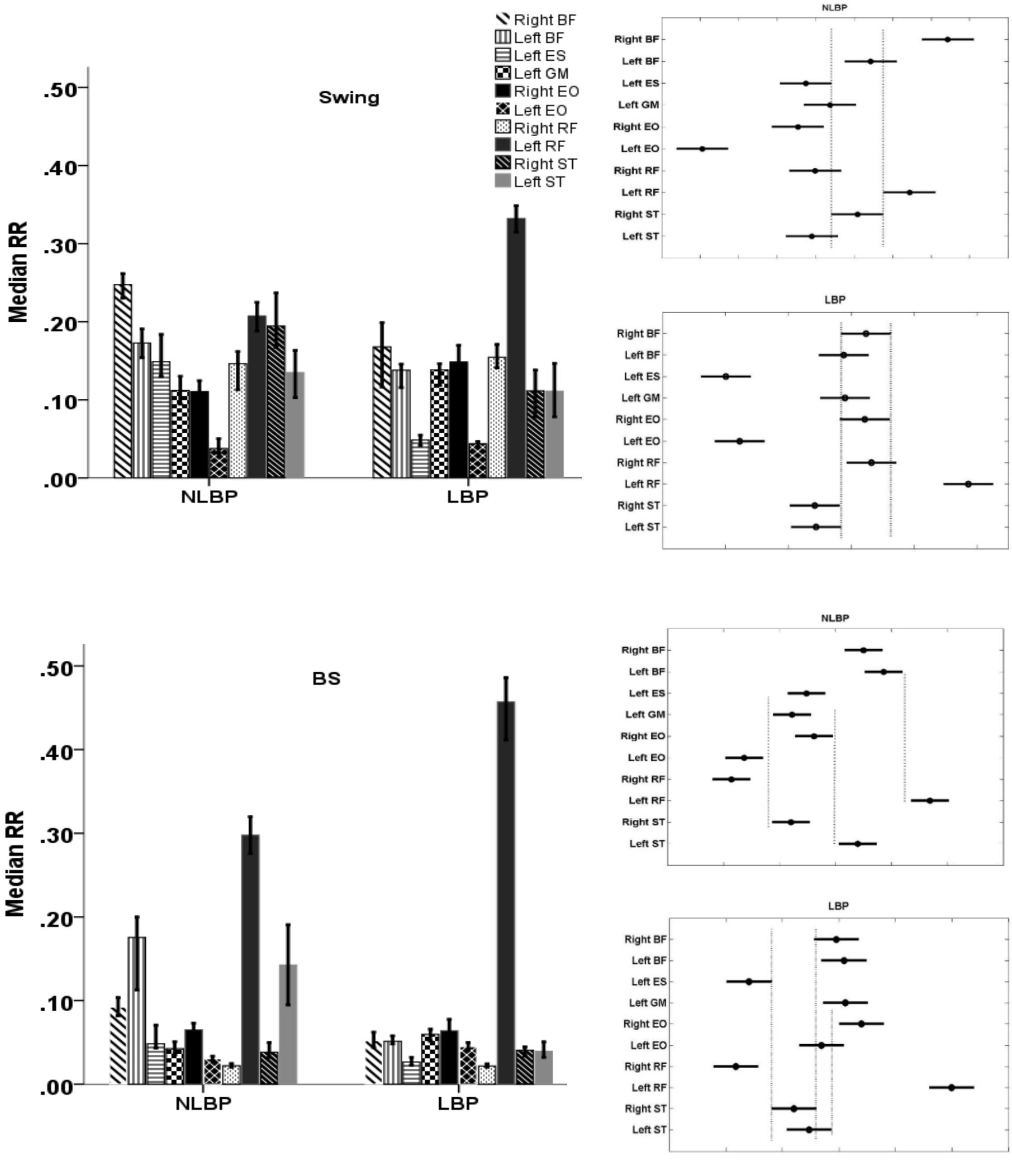


*Figura 5 [**Fig. 5.** LBP recurrence rate in the relevant phases. Error bars 95% C.I.]*

The BS and the DS also show a high capacity to discriminate the Hc, showing the BS higher accuracy. When this phase was isolated from the rest of the swing, the right EO and the hamstrings assume relevance and not the EO of the left side. The purpose of BS is to align and position the golfer's hub center and club head to boost to enhance the accuracy and speed in the downswing (Hume et al., 2005). At the peak of the BS, LHc golfers exhibit higher left shoulder horizontal adduction, right shoulder external rotation, and trunk rotation than HHc (Zheng et al., 2008). During the DS, LHc golfers have the largest angular velocities for the club shaft, right elbow and writs extension, as well as, angular displacement in trunk rotation (Zheng et al., 2008). Muscle change in the capacity to discriminate handicap expresses both different nervous strategies due the complexity of the task and the amount of information that combine eccentric and concentric contractions called stretch-shorten cycle.

3.4.3. Low back pain

BS is the phase where there is a greater discriminatory power to distinguish between LBP and NLBP golfers, achieving 100% of accuracy. When looking muscles alone, the left BF showed the higher accuracy at 99.3%. The BF arises from the ischial tuberosity and is responsible for the hip extension, knee flexion and participates in pelvic retroversion. Motor strategies program to facilitate these movements during the BS include left thigh extension, the lead side of right handed golfers. LBP golfers tended to flex their spines more when addressing the ball, showing greater left side bending during the BS (Lindsay and Horton, 2002). Also, they have less trunk extension strength at 60°/s and left hip adduction strength, as well trunk rotation angle toward the trail side (Lindsay and Horton, 2002; Tsai et al., 2010). During the BS, left hamstrings, left RF and right BF were the more discriminatory muscles, participating in extension and flexion of the thigh and hip. The neuromuscular strategies are limited by muscle length, since elite golfers with reduced hip flexor length reported more often that golf was affected by LBP (Evans et al., 2005). Golfers with history of LBP have limitations in the lead hip rotation and lumbar spine extension (Vad, 2004). However, the DS did not show the same relevance that swing and BS, i.e., for an accuracy above 85%, suggesting that for LBP groups, X-factor could be more crucial than the "X-Factor Stretch".

Contrary to what one would expect due the neuromuscular imbalance of ES in LBP subjects (Renkawitz et al., 2006), left ES did not show a discriminative power comparatively with the trunk rotators and thigh muscles. Cole and Grimshaw, (2008b) found that the LHc LBP golfers present lower ES activity than the LHc NLBP. Also, the LBP golfers activate ES early than NLBP players (Cole and Grimshaw, 2008a). Besides these results, the right ES presented higher activity than the left side (Cole and Grimshaw, 2008b), namely in the early DS. However, in the present study, the right ES was not monitored. The crunch factor (product between lateral bending and axial trunk rotation) is another parameter associated to LBP, although no significant differences between LBP with NLBP were found (Cole and Grimshaw, 2013).

As for Hc, the FT phase revealed no power to discriminate the two classes (LBM and NLBP), for any muscle, despite the fact that more swing-related injuries were reported (McHardy et al., 2007). Discrimination strategies in neuromuscular coordination were more prevalent during the BS.

3.5. Conclusions

The recurrence rate and the ratio between recurrence ratio and determinism are the two RQA features that showed higher discriminating power in SVM, for both for handicap and low back pain during the swing. The swing phase with higher discriminant power was the backswing for both handicap and low back pain. The hamstrings muscles, trunk rotators and left rectus femoris showed greater discriminant power for handicap, depending on the swing phase studied. The hamstrings and left rectus femoris showed higher discrimination for low back pain, and the lead side offers better major accuracy classification than the trail side, despite the downswing being the execution phase. Low back pain golfers show less neuromuscular coordination strategies than the golfers without low back pain. None of the muscles showed discriminative power during the follow-through, in both handicap and low back pain golfers.

Recurrence Quantification Analysis and Support Vector Machines showed a high performance, but the type of features extraction is not consistent between muscles, being muscle dependent for electromyography processing and normalization, as well as embedding parameters used in this study. The authors recommend that further studies examine the weight of different processing types and embedding parameters on the accuracy to discriminate different electromyography signals by groups. It is also recommended to combine kinematics and kinetics with electromyography to understand the relationship of those variations with motion parameters.

Acknowledges

The project “Neuromuscular activity in the golf swing with implications for the practice and in the prevention of overuse injuries” was supported by the Portuguese Foundation for Science and Technology (FCT) fund (PTDC/DES/105176/2008).

The authors want to thank to Professor Norman Marwan (PIK-Potsdam) for counseling.

References

Ashish A, Shweta S, Singh SJ. Comparison of lumbar and abdominal muscle activation during two types of golf swing: An EMG analysis. RICYDE. International Journal of Sport Science 2008;IV(12):59–71.

Boser BE, Guyon IM, Vapnik VN. A Training Algorithm for Optimal Margin Classifiers. In: Proceedings of the Fifth Annual Workshop on Computational Learning Theory 1992:144–152.

Burges C. A tutorial on support vector machines for pattern recognition. Data Mining & Knowledge Discovery 1998;2:121–167.

Cabri J, Sousa J, Kots M, Barreiros J. Golf-related injuries: a systematic review. European Journal of Sport Sciences 2009;9(6):353–66.

Castellini C, Smagt P van der. Surface EMG in advanced hand prosthetics. Biological Cybernetics 2009;100(1):35–47.

Castellini C, Smagt Pvan der, Sandini G, Hirzinger G. Surface EMG for force control of mechanical hands. In: IEEE International Conference on Robotics and Automation Pasadena, CA, USA, May 19-23, Pasadena 2008:725–730.

Cheetham PJ, Martin, PE, Mottram RE, Laurent, BFSt. The importance of stretching the "X-Factor" in the downswing of golf : The "X-Factor Stretch". In: Thomas PR, editor. Optimising Performance in Golf. Brisbane, Australia: Australian Academic Press, 2001:192–199.

Chu Y, Sell TC, Lephart SM. The relationship between biomechanical variables and driving performance during the golf swing. Journal of sports Sciences 2010;28(11):1251–9.

Cole M, Grimshaw P. Trunk muscle onset and cessation in golfers with and without low back pain. Journal of Biomechanics 2008a;41:2829–2833.

Cole MH, Grimshaw PN. Electromyography of the trunk and abdominal muscles in golfers with and without low back pain. Journal of Science and Medicine in Sport 2008b;11(2):174–81.

Cole MH, Grimshaw PN. The crunch factor's role in golf-related low back pain. Spine Journal 2013 Oct 12.

Cortes C, Vapnik V. Support-vector networks. Machine Learning. 1995;20(3):273–297.

Del Santo F, Gelli F, Schmied A, Vedel, J-P, Rossi A, Mazzocchio, R. Motor unit synchronous firing as revealed by determinism of surface myoelectric signal. Journal of Neuroscience Methods 2006;155(1):116–21.

Dobrowolski AP, Wierzbowski M, Tomczykiewicz K. Multiresolution MUAPs decomposition and SVM-based analysis in the classification of neuromuscular disorders. Computer Methods and Programs in Biomedicine 2012;107(3):393–403.

Eckmann J-P, Kamphorst OS, Ruelle D. Recurrence Plots of Dynamical Systems. Europhysics Letters 1987;4(9):973–977.

Enoka RM. Eccentric contractions require unique activation strategies by the nervous system. Journal of Applied Physiology 1996;81(6):2339–2346.

Evans K, Refshauge KM, Adams R, Aliprandi L. Predictors of low back pain in young elite golfers: A preliminary study. Physical Therapy in Sport 2005;6(3):122–130.

Farina D, Fattorini L, Felici F, Filligoi G. Nonlinear surface EMG analysis to detect changes of motor unit conduction velocity and synchronization. Journal of Applied Physiology 2002;93(5):1753–63.

Filligoi G, Felici F. Detection of hidden rhythms in surface EMG signals with a non-linear time-series tool. Medical Engineering & Physics 1999;21(6-7):439–48.

Fox E, Lindsay D, Vandervoort A. Musculoskeletal injury questionnaire for senior golfers. In: Science and Golf IV. Proceedings of the World Scientific Congress of Golf. St. Andrews, Scotland: Routledge 2002:88–99.

Gluck GS, Bendo, JA, Spivak JM. The lumbar spine and low back pain in golf: a literature review of swing biomechanics and injury prevention. The Spine Journal 2008;8(5):778–88.

Güler NF, Koçer S. Use of Support Vector Machines and Neural Network in Diagnosis of Neuromuscular Disorders. Journal of Medical Systems 2005;29(3):271–284.

Hall MA. Correlation-based Feature Selection for Machine Learning. University of Waikato, 1999.

Hermens HJ, Merletti, Freriks B. European Activities on Surface Electromyography. European Activities on Surface Electromyography. In: Proceedings of the first general SENIAM workshop. SENIAM project, 1996.

Horton JF, Lindsay DM, Macintosh BR. Abdominal muscle activation of elite male golfers with chronic low back pain. Medicine and Science in Sports and Exercise 2001;33(10):1647–54.

Hsu C, Chang C, Lin C. A practical guide to support vector classification. 2003-2010; retrieved from https://www.cs.sfu.ca/people/Faculty/teaching/726/spring11/svmguide.pdf

Hume PA, Keogh J, Reid, D. The role of biomechanics in maximising distance and accuracy of golf shots. Sports Medicine 2005;35(5):429–49.

Ikegawa S, Shinohara M, Fukunaga T, Zbilut JP, Webber Jr CL. Nonlinear time-course of lumbar muscle fatigue using recurrence quantifications. Biological Cybernetics 2000;82:373–382.

Lei M, Meng G. Nonlinear Analysis of Surface EMG Signals. In: Lei M, Meng G, editors. Computational Intelligence in Electromyography Analysis - A Perspective on Current Applications and Future Challenges. INTECH 2012:119-174.

Lindsay D, Horton J, Vandervoort A. A review of injury characteristics, aging factors and prevention programmes for the older golfer. Sports Med 2000;30(2):89–103.

Lindsay D, Horton J. Comparison of spine motion in elite golfers with and without low back pain. J Sports Sci 2002;20(8):599–605.

Marwan N, Thiel M, Nowaczyk NR. Nonlinear Processes in Geophysics Cross recurrence plot based synchronization of time series. Nonlinear Process Geophys 2002; 2(9):325–331.

Marwan N, Carmenromano M, Thiel M, Kurths J. Recurrence plots for the analysis of complex systems. Phys Rep. 2007;438(5-6):237–329.

McHardy AJ, Pollard HP, Luo K. Golf-related lower back injuries: an epidemiological survey. Journal of Chiropractic Medicine 2007;6(1):20–6.

Renkawitz T, Boluki D, Grifka J. The association of low back pain, neuromuscular imbalance, and trunk extension strength in athletes. The Spine Journal 2006;6(6):673–83.

Shi J, Zheng Y, Chen X, Xie H. Modeling the relationship between wrist angle and muscle thickness during wrist flexion-extension based on the bone-muscle lever system: a comparison study. Medical Engineering & Physics 2009;31(10):1255–60.

Silva L, Marta S, Vaz J, Fernandes O, Castro MA, Correia-Pezarat P. Trunk muscle activation during golf swing: Baseline and threshold. Journal of Electromyography & Kinesiology 2013;23(5):1174–1182.

Sultornsanee S, Zeid I, Kamarthi S. Classification of Electromyogram Using Recurrence Quantification Analysis. Procedia Computer Science. 2011;6:375–380.

Tavakolan M, Xiao ZG, Menon C. A preliminary investigation assessing the viability of classifying hand postures in seniors. Biomed Eng Online 2011;10(1):79.

Tolambiya A, Thomas E, Chiovetto E, Berret B, Pozzo T. An ensemble analysis of electromyographic activity during whole body pointing with the use of support vector machines. PLoS One. 2011;6(7):e20732.

Tsai Y-S, Sell TC, Smoliga JM, Myers JB, Learman KE, Lephart SM. A comparison of physical characteristics and swing mechanics between golfers with and without a history of low back pain. The Journal of Orthopaedic and Sports Physical Therapy 2010;40(7):430-438.

Vad VB. Low Back Pain in Professional Golfers: The Role of Associated Hip and Low Back Range-of-Motion Deficits. American Journal of Sports Medicine 2004;32(2):494–497.

Vapnik VN. An Overview of Statistical Learning Theory. IEEE Transactions on Neural Networks 1999;10(5):988–999.

Webber Jr CL, Zbilut JP. Dynamical assessment of physiological systems and states using recurrence plot strategies. Journal of Applied Physiology 1994;76(2):965-973.

Zheng N, Barrentine SW, Fleisig GS, Andrews JR, States U. Kinematic analysis of swing in pro and amateur golfers. International Journal of Sports Medicine 2008;29(6):487–93.

Zhao Z, Morstatter F, Sharma S, Alelyani S, Anand A, Liu H. Advancing feature selection research-ASU feature selection repository. Arizona State University, 2010. Retrieved from http://www.public.asu.edu/~zzhao15/papers/TR-10-007%20Zhao,%20Morstatter,%20Sharma,%20Aleyani,%20Anand,%20and%20Liu.pdf

Ziai A, Menon C. Comparison of regression models for estimation of isometric wrist joint torques using surface electromyography. Journal of Neuroengineering and Rehabilitation 2011;8(1):56.