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Short communication

Classification methods can identify external constrains in swimming

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ABSTRACT

The purpose of the present study is to examine whether the use of fins is identifiable based on swimmers' technique and to find out technique-related features that depict fins' influence. First, a number of features were extracted from kinematic data given by movement sensors attached to swimmers' bodies during butterfly swimming technique. Then, dimensionality reduction, feature selection and classification methods were applied to the extracted features. Two classification tasks were defined, one for the three classes of long, short and no fins, attaining accuracy up to 70, 62 and 70%, respectively, and the two-class simplified version (long fins, no fins) with accuracy up to 78%. These high accuracy levels were also found statistically significant and suggest that the use of fins influences swimming technique in a recognizable way and that the selected features that depict those differences are swimming type depended.

1. Introduction

The reduction and interpretation of multimodal data (Poon et al., 2015) is a contemporary methodological challenge. To utilize such data in movement analysis, pattern recognition techniques, like feature selection and classification algorithms (Tang et al., 2014), are combined to identify differences among athletes e.g. based on gender (Phinyomark et al., 2014; Phinyomark et al., 2016), age (Begg & Kamruzzaman, 2005), experience level (Jensen et al., 2012) or training conditions/equipment (Lau et al., 2008; Eskofier et al., 2012).

Butterfly swimming technique represents the simultaneous movement of upper and lower limbs, where for one upper limb cycle there are two lower limb movements and a wipe-like dolphin movement of head and trunk. Yet, the individual movement pattern is affected by factors like physical characteristics and level of expertise, all of which comprise the personalized swimming technique. Swimming movement is sensitive to constraints (Schnitzler et al., 2011; Averianova et al., 2016) that contribute to the movement pattern (Newell, 1986). Fatigue can also compromise efficiency (Figueiredo et al., 2011). In any case, a slide alteration of an individual's competitive swimming pattern may constitute the discriminative factor for achieving or not the maximum result (Takagi et al., 2004).

Considering butterfly swimming, training with fins for facilitation of technique learning or/and improvement of physical features is common. Yet, swimming with fins consists a similar but not the same pattern with swimming competitively (Averianova et al., 2016), at least under the perspective of averaging the whole trial. Therefore, distinguishing the influence of a task specific constraint like fins in butterfly swimming technique, may be useful in training practice. The large surface of fins compared to foot surface and the stiffness of the material, may represent an extra load which can act as a task constraint. This could depend on time (Newell, 1986), affect the technique (Seifert et al., 2014) and differentiate the propulsion effectiveness (Abraldes et al., 2010). In this context, training syndromes, such as overuse, or training "mistakes", such as lack of specification or overload, can be provoked by training equipment widely used in swimming (Matos et al., 2013).

The purpose of the present study is to examine whether the use of fins is identifiable based on the swimmers' technique using machine learning tools and to find technique-related features that depict fins' influence.

2. Material and methods

Twenty-three swimmers, 13 boys and 10 girls aged 15.8 ± 1.7 years, voluntarily participated in this study. They were active national level swimmers, with at least six years of training experience, during which they used fins at most of their training sessions. The study was approved by the ethics committee of the institution and all participants signed a consent form before their participation. The measurements were held in a 50 m indoor swimming pool. After a common warm up (600 m), participants

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performed 3×50 m sprint butterfly. One trial was without fins and two with fins, 5–8 cm and 23–26 cm blade respectively, with a 15 min interval between them. No specific instruction about the breathing rhythm was given to avoid putting any constrains to the organization of their movement. The tests were performed in random order.

Kapa-Swim sensors (Kapa-Invent, © 2014) (Averianova et al., 2016) were fixed on the swimmers' upper trunk (C7) and pelvis (acquisition frequency 200 Hz and 2nd order low pass Butterworth filter at 15 Hz). An example of the original data is shown in Fig. 1. Firstly, the time-series of the x-component of angular velocity was truncated in both edges to isolate the butterfly swimming technique. The truncation points were determined automatically from the zero level of angular velocity before the first peak, signifying the start of periodic-like oscillations (for the left edge) and after the last peak, signifying the end of these oscillations (for the right edge). Each trunk and pelvis truncated time-series was then integrated to obtain angular displacement and smoothed with high-order moving average filter to remove the systematic drift of gyroscope.

A set of features in the time and frequency domain was extracted from the angular displacement of trunk and pelvis time-series, considered as the most descriptive of the butterfly swimming technique. The procedure was automated using Matlab (The MathWorks, Inc., Natick). The extracted features were separated in two categories. The first category contains static characteristics of the entire time-series. The features of the second category were extracted using variable size sliding time-windows to account for the influence of time on the movement patterns. The windows were integral multiples of the oscillation periods, i.e. one (w = 1), two (w = 2) and three (w = 3) periods. All 151 extracted features (Table 1) were derived from ten core features on the trunk and pelvis time-series and the different time-frames.

Some of the extracted features are defined in terms of the points of structural changes in the series of core features. The critical points were captured using an adjusted version of the change detection method CUSUM (Barnard, 1959). More specifically, the CUSUM algorithm implemented in Matlab was adjusted by replacing the stopping criteria for the detection of 'critical points' with the following two:

- In case Upper Control Limit (UCL) and Lower Control Limit (LCL) both take successive zero values, the critical point is set as the first time point where UCL and LCL become different from zero. (CUSUM type 1, Fig. 2)
- In case UCL takes successive zero values while LCL is non-zero, followed by a part of the sequence where LCL takes successive zero values while UCL is non-zero (and vice versa), critical point is set as the first time point between the interval that UCL becomes different from zero and LCL becomes zero. (CUSUM type 2, Fig. 2)

The original number of features was considered too big compared to the actual available sample (151 and 69, respectively). Moreover, formal statistical analysis (3×2 repeated measures ANOVA for the three fins levels and the two gender levels) for each

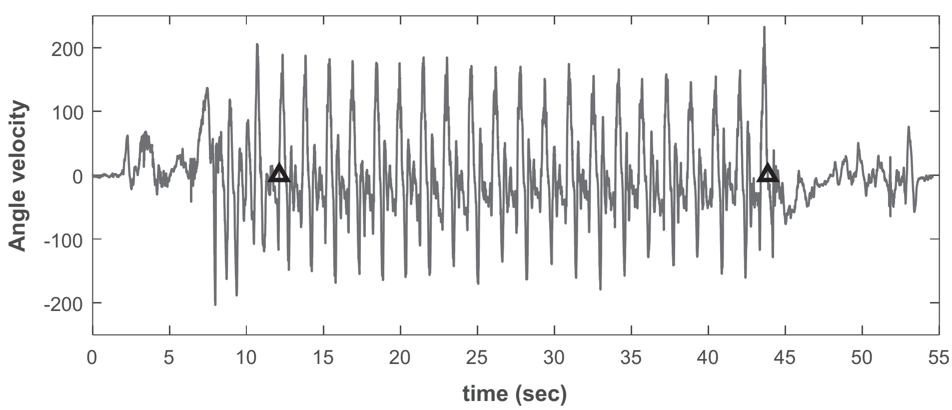

Fig. 1. Example of the raw angular velocity time-series and the left and right truncation points denoted by triangles.

Table 1
Description of the ten core features used as basis for feature extraction.

	Features	Calculation methodology
TIME DOMAIN FEATURES	Oscillation frequency	The inverse of oscillation period (in strokes / min), where oscillation period is time between successive peaks of the time-series
	Phase difference between trunk and pelvis time series	The difference of the time between the trunk time-series peaks and the pelvis time-series peaks (they do not occur at the exact same instances)
	Angle range	The difference of the highest angle minus the lowest angle observed in the examined time-period (i.e. the whole time series or a specific window frame)
FREQUENCY DOMAIN FEATURES	Main frequency	The frequency with the highest signal proportion in the PS
	Signal proportion in main frequency of PS	The signal proportion in the main frequency of the PS
	Frequency range with a specific proportion (x%) of signal in Power Spectrum (PS)	The minimum frequency range that contains the x% (90%, 95%, 99%) of the signal total energy in the PS (calculated using recursive algorithm)
	Area of PS	The surface area of the whole PS which is above a minimum threshold (the threshold is used to eliminate frequencies of negligible power)
	Frequency range of main peak of PS	The frequency range between the starting and ending frequency of the main peak of the PS
	Area of main peak of PS	The surface area of the PS within the main frequency peak
	Number of peaks in PS	Number of local maxima in the power spectrum

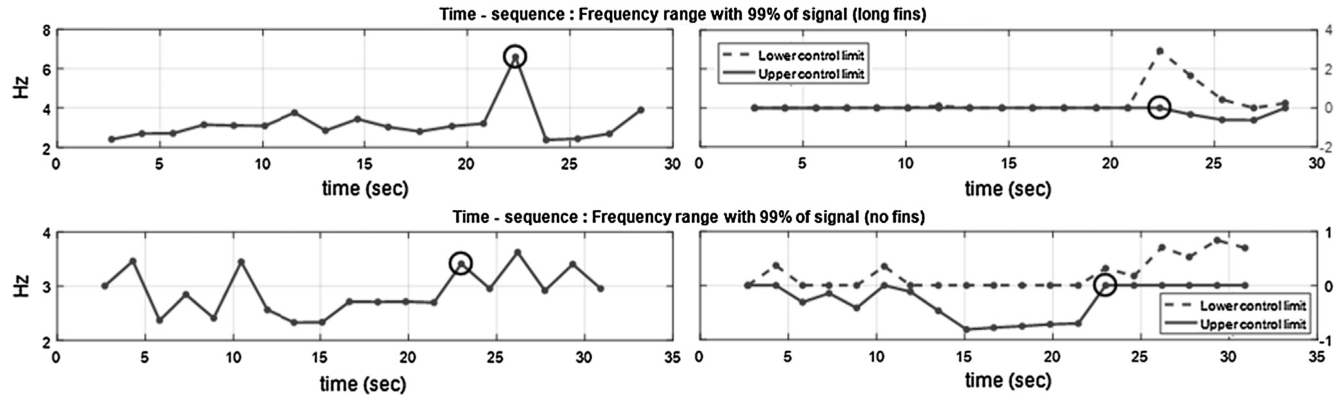

Fig. 2. upper part: CUSUM type 1 example, lower part: CUSUM type 2 example.

of the 151 features resulted in only 25 statistically significant at $\alpha = 0.05$ and 37 at $\alpha = 0.10$. Thus, many of the features may not be relevant to the classification task on the fins levels.

To reduce the dimensionality of the feature space for the classification problem four popular dimensionality reduction techniques were employed to determine the one that performs best for the actual problem: Fisher Score, ReliefF (with 10 nearest neighbours), Support Vector Machines with Recursive Feature Elimination (SVM-RFE) and Principal Component Analysis (PCA) (Liu & Motoda, 2007). The binary classification tree method (BCTM) (Breiman, 2017) was used for accessing the output of ReliefF, Fisher score and PCA.

For each feature selection technique, the optimal feature subset of increasing cardinality was obtained, as shown in Fig. 3, where the classification error rate of SVM-RFE (dashed line) has a local minimum at cardinality 11 (three fins levels). Indeed, when the same classification is tested using leave-one-out cross-validation, the error tends to increase when more than 11 features are used (solid line in Fig. 3). In cases where the selected feature subset cardinality was larger than 20, the cost-efficient optimal (minimal misclassification error with lower than 20 features) was used. In addition, for ReliefF and Fisher score giving large feature subsets, further dimension reduction using PCA was attempted, denoted ReliefF + PCA and Fisher score + PCA, respectively. The methods were compared with each other using the McNemar's test (Bostanci & Bostanci, 2013), which assesses the statistical significance of the difference of the misclassification errors of the two methods. The scenario with all the 151 features (All-in) was also included for comparison purposes.

In total, 6 different classification models were assessed for the two-class scenario (adding ReliefF + PCA and Fisher score + PCA) and 5 for the three-class scenario (adding ReliefF + PCA). Due to the small size of available data, leave-one-out cross-validation technique was used to verify the classification models. The statistical significance of the classification accuracy with each method was assessed using the multiple permutations method (Golland et al., 2005). The permutations were applied on the dataset before the feature selection. The performance of the selected classification model was further assessed computing the performance metrics Accuracy, Precision, Recall, F-measure and Approximate Correlation (AC) (Baldi & Brunak, 2001). All the computations were performed in Matlab. The sketch of the whole procedure is shown in Fig. 4.

3. Results

The cross-validation accuracy of each examined technique with the optimal number of features is presented in Table 2. The dimension reduction technique with best performance for the two-class scenario is Fisher score using a subset of 13 features, improving the accuracy of All-in by 6.5%, whereas ReliefF has the worst

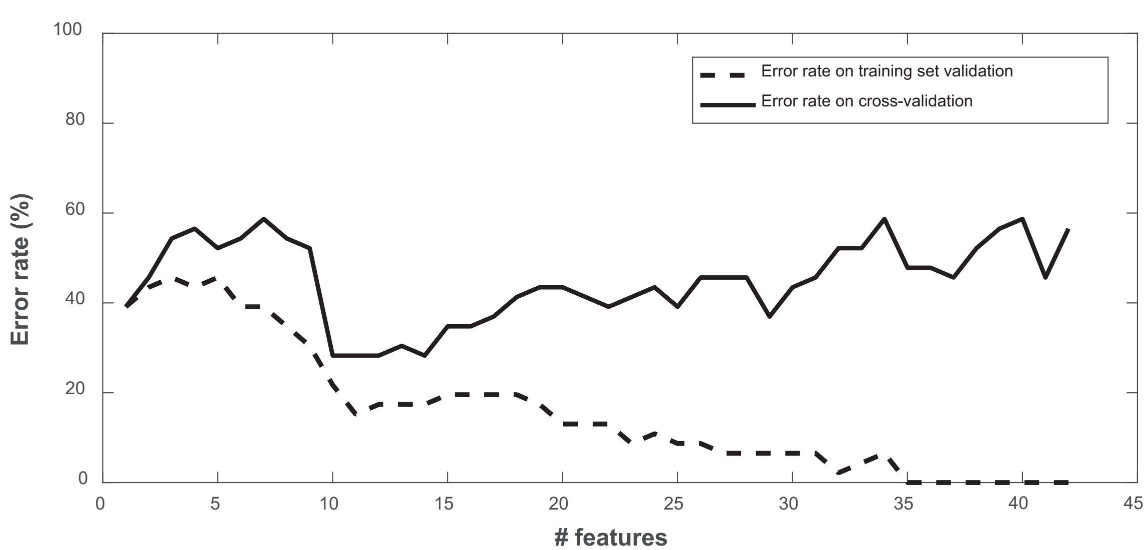

Fig. 3. SVM-RFE error rate as a function of the feature subset cardinality for the two classification settings as shown in the legend for the three-class classification problem.

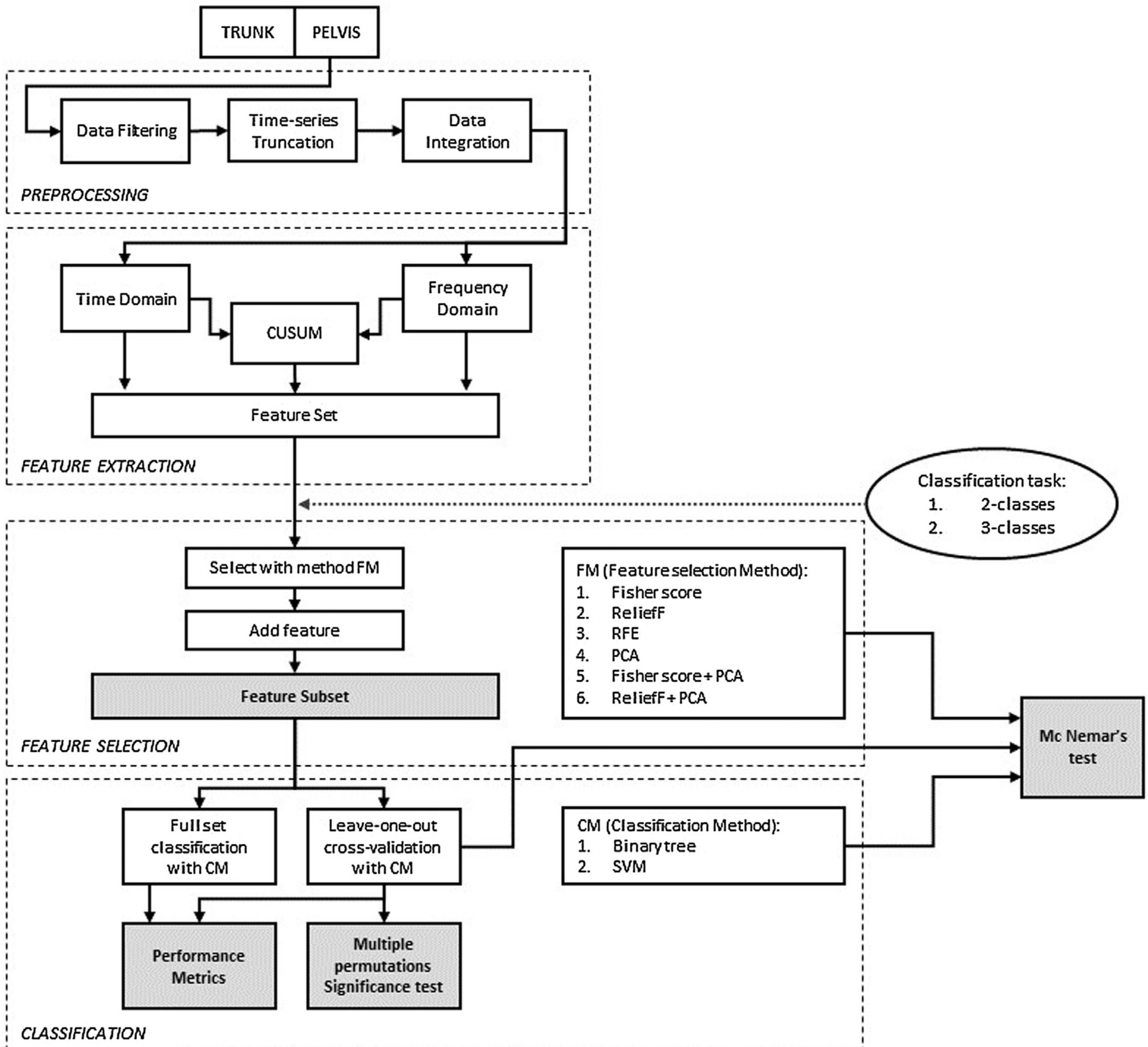

Fig. 4. Step-by-step methodology summary.

performance (statistically non-significant accuracy). For the three-class scenario, only the best performing SVM-RFE of 11 features possesses statistically significant accuracy for all three classes, which is much higher than All-in for the classes "long" and "short", but not for the class "no". These differences in the accuracy of the methods are supported by the McNemar's test, at $\alpha = 0.05$ for the Fisher score in the two-class scenario, and at $\alpha = 0.01$ for the SVM-RFE in the three-class scenario.

Table 3 shows the performance metrics based on the feature set determined by Fisher Score. The accuracy of the classification with

Table 2
Accuracies of classification with different dimension reduction techniques, two-class and three-class scenarios, statistical significances depicted using stars (*: 90% significance level, **: 95% significance level, ***: 99% significance level).

Dimensionality reduction technique	Accuracy, two-class scenario	Accuracy, three-class scenario		
		'long'	'short'	'no'
All-in	71.74%**	52.17%	42.03%	78.26%**
PCA	76.09%**	62.32%	59.42%	56.52%
Fisher Score	78.26%**	55.07%	57.97%	79.71%**
Fisher + PCA	n/a	69.57%	47.83%	52.17%
ReliefF	36.96%	60.87%	55.07%	59.42%
ReliefF + PCA	54.35%	62.32%	44.93%	42.03%
SVM-RFE	71.74%***	69.57%***	62.32%***	69.57%***

Table 3
Best classification method performance metrics, two-class scenario (Fisher Score - BCTM).

	Training set		Leave-one-out cross-validation	
	'with'	'without'	'with'	'without'
#misclassified cases	2	1	5	5
Accuracy	93.48%		78.26%	
AC	93.52%		78.26%	
Precision	95.45%	91.67%	78.26%	78.26%
Recall	91.30%	95.65%	78.26%	78.26%
F-measure	93.33%	93.62%	78.26%	78.26%

Table 4
Best classification method performance metrics, three-class scenario (SVM - RFE).

	Training set			Leave-one-out cross-validation		
	'long'	'short	'no'	'long'	'short'	'no'
#misclassified cases	5	5	3	7	9	7
Accuracy	78.26%	78.26%	85.51%	69.57%	62.32%	69.57%
Precision	66.67%	68.18%	78.26%	54.17%	42.11%	53.85%
Recall	69.57%	65.22%	78.26%	56.52%	34.78%	60.87%
F-measure	68.09%	66.67%	78.26%	55.32%	38.10%	57.14%
AC	75.82%	75.29%	83.70%	66.14%	55.74%	66.92%

Table 5
Most important features identified according to best performance classification models.

IDENTIFIED IMPORTANT FEATURES	
Two-class scenario	**Three-class scenario**
Frequency range with 95% of signal in power spectrum, trunk time-series (Hz)	Frequency value on critical time point, trunk (strokes per minute)
Signal proportion in main frequency of power spectrum, pelvis time-series (%)	Average frequency of trunk time -series (strokes per minute)
Area of main peak of window-power spectrum on critical point, trunk time-series, w = 2	Average frequency of pelvis time -series (strokes per minute)
Main frequency value on critical point, trunk time-series, w = 2	Angle range in trunk timer-series
Frequency on critical time point, pelvis (strokes per minute)	Angle range in pelvis time-series
Main frequency value on critical point, trunk time-series, w = 3	Average angle range per period, trunk time-series
Signal proportion in main frequency of power spectrum, trunk time-series (%)	Window-angle range value on critical point, trunk time-series, w = 1
Area of main peak of window-power spectrum on critical point, trunk time-series, w = 3	Window-angle range value on critical point, trunk time-series, w = 2
Area of window-power spectrum at critical point, trunk time-series, w = 1	Window-angle range value on critical point, pelvis time-series, w = 2
Critical point on sequence of main frequency of window-power spectrum, trunk time-series, w = 1	Window-angle range value on critical point, trunk time-series, w = 3
Window-angle range value on critical point, pelvis time-series, w = 3	Window-angle range value on critical point, pelvis time-series, w = 3
Critical point of sequence of area of main peak of window-power spectrum, pelvis time-series, w = 3	
Critical point on sequence of number of peaks in window-power spectrum, trunk time-series, w = 1	

the selected features on the training set is very high, over 93%, and remains high at 78% for leave-one-out cross validation (for this case, it happens that both true positives and negatives equal 18 while false positives and negatives equal 5 giving the same value for the four performance measures). The performance metrics of SVM-RFE method for the three-class scenario are shown in Table 4. This classification task is more difficult and again the accuracy for leave-one-out cross-validation, though smaller than for the training set, is still relatively high. Finally, the 13 features identified as most important by Fisher score algorithm for the two-class scenario and the 11 features selected by SVM-RFE for the three-class scenario are shown in Table 5.

4. Discussion

The high performance metrics for both scenarios indicate that the mathematical models created can be considered successful. In the two-class scenario, the classification accuracy is as high as 78% and the misclassified cases are balanced in the two classes in both the training and cross-validation set. The classification performance of the three-class scenario appears to be lower, but still all metrics are distinctly higher compared to the baseline random model (37, 29 and 37% higher accuracy for each class). In both scenarios, the acquired accuracy was statistically significant at the $\alpha = 0.05$ level. The existence of a mathematically successful classification model proves that fins indeed influence the swimmers' technique in a recognizable way that is captured by the extracted features.

As shown by the accuracy metrics for the three-class scenario, the class 'short' (short fins) was the most difficult to identify. Also, some techniques (Fisher Score, All-in) obtaining high accuracy in identifying no fins performed lower for the other two classes, showing that although they can be used for the identification of cases with high dissimilarities, they fail to detect cases with smaller differences, such as the size of fins. The trigger point could be the surface area (Zamparo et al., 2006), being 1.7 times larger for small fins and 3.3 for long fins than the barefoot surface. Long fins alter kick depth, drag and energy cost (Zamparo et al., 2002; Zamparo et al., 2006) and thus affect trunk and pelvis kinematic features (Averianova et al., 2016), whereas small fins may not impose exemplar constrains in the movement making the identification more difficult. Fin type affects also the hydro mechanical efficiency and the swimming technique (Nicolas et al., 2010). However, if the swimmer can gain in training goals, then the use of small fins serves better the training principle of specificity (Toussaint & Vervoorn, 1990).

The optimal features for the two-class and three-class scenarios do not present a high overlap, showing that different features are important for a more general (existence of fins) and a more detailed (type of fins) approach. The presence of features derived from time-windows implies that there is rather abrupt state alteration than "steady state" of decay or growth of a pattern and often the same characteristic is found important at different time-windows, e.g. area of main peak of window-power spectrum and main frequency on critical point on trunk time-series. These findings are in line with reports about critical points signifying transitions of movement coordination (Kelso et al., 1986), which could be considered as a constraint led change (Haudum et al., 2012). This evidence has physical meaning regarding the appropriate time or distance of training with long fins and gives a perspective of handling the data (Cazzola et al., 2016; Mullineaux & Irwin, 2017).

The persistence of frequency characteristics (11 of 13 optimal features for two-class) may be attributed to their power in discriminating movement patterns in gait (Giakas et al., 1996) and swimming (Tella et al., 2008). Indeed, frequency-based features are considered more effective for classification (Englehart et al., 1999). For the three-class scenario, 8 out of 11 features are related with angle-range, showing its importance for the identification of the three classes.

The fins seem to influence more the trunk than the pelvis movement as most of the optimal features are from trunk time-series (9/13 in the two-class and 7/11 in the three-class scenario). This is in line with Averianova et al. (2016), showing that the pelvis has low dimensionality, unaffected by fins, while trunk is more sensitive in increasing local dynamic stability. Yet, trunk is more prone to drug, hence this must be taken into consideration from coaches and swimmers, which should try to keep the competitive butterfly swimming technique of the trunk when swimming with fins.

Concluding, the use of fins is identifiable based on the swimmers' technique. Therefore, fins should be used under the perspective that they influence the selected from the analysis technique-related features.

Conflict of interest statement

I would like to confirm that there is no conflict of interest in the submitted manuscript.

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