MOTOR MODULARITY DURING PEDALLING ACROSS DIFFERENT MECHANICAL CONSTRAINTS: A TIME-FREQUENCY ANALYSIS

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The purpose of this study was to determine the changes in the time-frequency-muscle synergies across different mechanical constraints during pedalling. Eleven experienced cyclists performed three 1-min bouts of pedalling at 90 revolutions per minute: bilateral (250 W), unilateral (125 W) and effective (250 W). Surface electromyographic (EMG) records from eleven lower-limb muscles were used to extract muscle synergies based on linear envelope (LE) or based on time-frequency features (TF). Three LE muscle synergies accounted for a mean variance accounted for (VAF) of 91.0 % ± 2.3, 90.7 % ± 2.4 and 91.6 % ± 2.4, for the bilateral, unilateral and effective pedalling tasks, respectively. When three TF muscle synergies were extracted, similar muscle groupings were obtained. The main results support the neural origin of the motor modularity.

KEYWORDS: muscle synergies, motor control, pedalling effectiveness.

INTRODUCTION: The modularity of motor control, by means of a limited number of muscle synergies (or motor modules), has been subjected to a growing body of investigations during the last decade, but its neural origin is still debated or at least misunderstood. The neural hypothesis supposes that the motor behaviours are built from the recruitment of a low number of hard-wired muscle synergies into the spinal motoneuronal network (Frère, 2017). Recently, it has been proposed to account for the spectral properties of the electromyographic (EMG) signals to assess if the muscles of one synergy shared a common time-frequency pattern (Frère, 2017). While the first results of these time-frequency-muscle synergies agreed with the neural hypothesis of the motor modularity, it remains to verify their robustness under different mechanical constraints.

To this aim, the pedalling task is a useful paradigm as it is easy to vary and control the mechanical constraints, such as the power output or the pedalling cadences. Previously, it has been shown that the muscle synergies were consistent while torque, velocity and posture were manipulated during pedalling (Hug et al., 2011). Also, the bilateral nature of the pedalling task might alter the coordination, as the upstroke phase of the pedalling cycle might be compensated by the concomitant propulsive phase of the contralateral limb. Indeed, changes in the muscle activation and coordination have been observed when a pull-up action on the pedal was necessary to achieve the pedalling cycle (Mornieux et al., 2010). However, the spectral properties of the EMG signals were not investigated.

Therefore, the aim of the current study was to determine the changes in the time-frequency-muscle synergies across different mechanical constraints during pedalling. It was hypothesised to detect a change in the composition of the time-frequency-muscle synergies due to the active or passive pull-up action during the upstroke phase of the pedalling cycle.

METHODS: Eleven experienced (national level) male cyclists volunteered to this study (height: 179 cm ± 5, mass: 72.8 kg ± 5). After a 5-minute warm-up at 100 Watts with a pedalling rate of 90 revolutions per minute (rpm), participants randomly performed three trials at 90 rpm, lasting 1 minute each. One trial consisted of a bilateral pedalling task at 250 W while the second one was a unilateral task with the right leg at 125 W. During the last trial, called "effective" (90 rpm at 250 W), participants were asked to keep the tangential force positive during the upstroke, using a continuous feedback of this pedal force component, which forced cyclists to pull up on the pedal during this phase (Mornieux et al., 2010). 3-minute of active recovery in between trials was allocated.

Both right and left cranks of the electro magnetically braked SRM® ergometer (Schoberer Rad Messtechnik, Welldorf, Germany) were equipped with the Powerforce® pedal forces

measurement system (Radlabor, Freiburg, Germany), to measure and represent tangential pedal force components.
The activity of 11 muscles of the right side of the body was simultaneously recorded: *tibialis anterior* (TA), *soleus* (SOL), *gastrocnemius lateralis* (LG) and *medialis* (MG), *vastus lateralis* (VL) and *medialis* (VM), *rectus femoris* (RF), *tensor fascia latae* (TFL), *biceps femoris* (long head, BF), *semitendinosus* (ST) and *gluteus maximus* (G_{max}). The EMG activity was recorded using wireless electrodes (Delsys Trigno™, Boston, MA). The electrodes were placed longitudinally with respect to the underlying muscle fibre arrangement and were located according to SENIAM recommendations (Hermens et al., 2000). Before applying electrodes, the skin was shaved and cleaned with alcohol to minimize impedance. Raw EMG signals were preamplified (gain 300, bandwidth 20-450 Hz) at a sample rate of 2000 Hz. One triaxial accelerometer (sampling rate 148.18 Hz; Delsys Trigno™, Boston, MA) was placed on the opposite crank (left side) to determine the top dead centre of the pedal revolution.
Muscle synergies were extracted in two different ways: (i) linear envelope (LE) muscle synergies as classically done in the literature and (ii) time-frequency (TF) muscle synergies. For the LE muscle synergies, raw EMG signals were band-pass filtered (zero lag, 5-450 Hz, Butterworth filter, 4th order), rectified and then low-pass filtered (zero lag, 6 Hz, Butterworth filter, 4th order). For each muscle and pedalling cycle (n=15), the envelope was time- and amplitude-normalized (200 data points with values ranging between 0 and 1). The initial data matrix was thus an 11-row and 3000-column matrix. Then, the non-negative matrix factorization (NMF; Lee & Seung, 2001) was used to obtain the muscle synergies composed with the muscle synergy vectors matrix (also called motor modules, **W**) and the synergy activation coefficients matrix (also called motor primitives, **C**).
For the TF muscle synergies, after being band-pass filtered (as for LE approach), EMG recordings were processed across a wavelet filter bank with a nonlinear scale function (von Tscharner, 2000). The wavelet transformation of the EMG signal resulted on a time-frequency map of 11 wavelet intensities. For each muscle and pedalling cycle, the whole TF map was interpolated to 200 time points and normalized to its peak value. Therefore, the initial data matrix was a 11-row (number of wavelets), 3000-column (15 cycles of 200 time points) and 11-layer (number of muscles) matrix. A canonical decomposition–parallel factor analysis (CANDECOMP-PARAFAC) was performed with the N-way toolbox for Matlab (Anderson & Bro, 2000) to extract the TF muscles synergies.
The number of muscle synergies to extract was determined according to the least number of muscle synergies that accounted for >90% of the variance accounted for (VAF; Hug et al., 2011). To assess the similarity of the extracted muscle synergies between the both methods (LE vs. TF muscle synergies), across the three pedalling tasks, one-dimensional statistical parametric mapping (SPM; Pataky, 2012) tests were used. A two-way ANOVA (extraction methods × pedalling task; α = 0.05) with repeated-measures on one factor (pedalling task) was performed on **W**. *Post-hoc* Student *t*-tests were used in case of significant main effect (α = 0.05/3 = 0.017). One interest of this statistical approach, beyond the effects of the factors, was to precisely detect which muscle weightings significantly change. No statistical analysis was performed on **C** due to their different structures (time-series *vs.* TF representation).

RESULTS: Three LE muscle synergies were extracted for the three pedalling tasks. Briefly, the first muscle synergy (**W**#1) mainly implied hip (G_{max}), knee (VL, VM and to a lesser extent RF) and ankle plantarflexor (SOL) muscles during the downstroke phase of the pedalling cycle (Figure 1). The second muscle synergy (**W**#2) occurred at the second part of the downstroke phase and at the beginning of the upstroke phase. This synergy mainly involved hip extensor (BF, ST and to a lesser extent G_{max}) and plantarflexor (LG, MG and SOL) muscles. Finally, the third synergy (**W**#3) is activated during the upstroke phase up to the very beginning of the downstroke phase of the following pedalling cycle. Such muscle synergy relied on the dorsiflexor (TA) and hip flexor (RF and TFL) muscles.These three muscle synergies accounted for a mean VAF of 91.0 % ± 2.3, 90.7 % ± 2.4 and 91.6 % ± 2.4, for the bilateral, unilateral and effective pedalling tasks, respectively. There was no evidence of a main effect ($F_{2,20}$ = 1.13, p = 0.34) of the pedalling tasks on the VAF values.

Three time-frequency-muscle synergies were also extracted for the three pedalling tasks. Grossly, the motor modules (Figure 1) appeared to be similar to those obtain with the LE method. Statistically, in terms of similarity of the muscle synergy vectors, solely a main effect (p = 0.032) of the mechanical constraints has been identified for **W**#1 (Figure 2), especially for the RF muscle. A main effect of the methods (p = 0.002) of synergies extraction have been detected for **W**#2. More specifically, *post-hoc t*-test showed that, BF, ST and G_{max} weightings were lower with the TF approach in comparison with the LE method, whatever the pedalling constraint (Inset Figure 2). For the last synergy (**W**#3), neither main effects nor interaction effect were found suggesting a similar composition across the methods of extraction and task constraints.

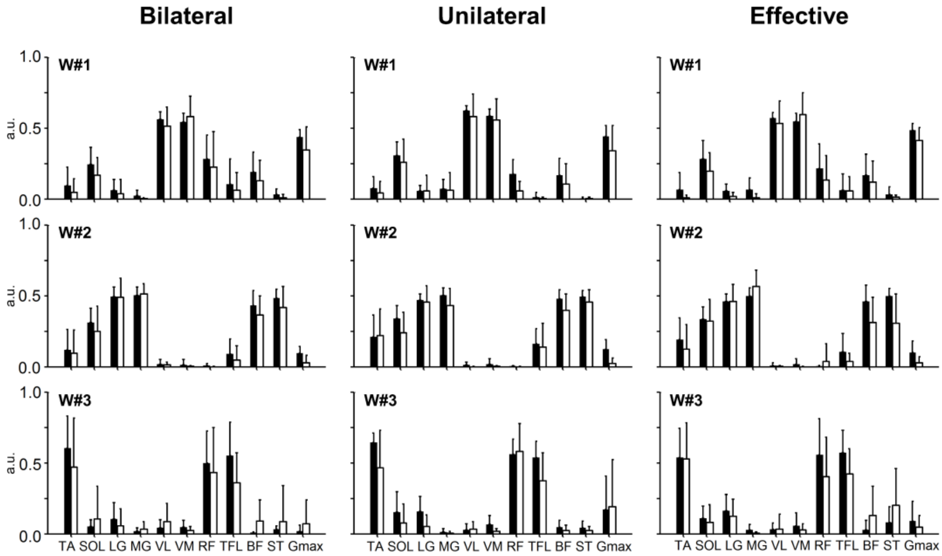

Figure 1: Ensemble averages (+ 1 SD) of the compositions of the three motor modules extracted across the three pedalling tasks and from both methods. Black bars: muscle weightings from the LE method; White bars: muscle weightings from the TF method.

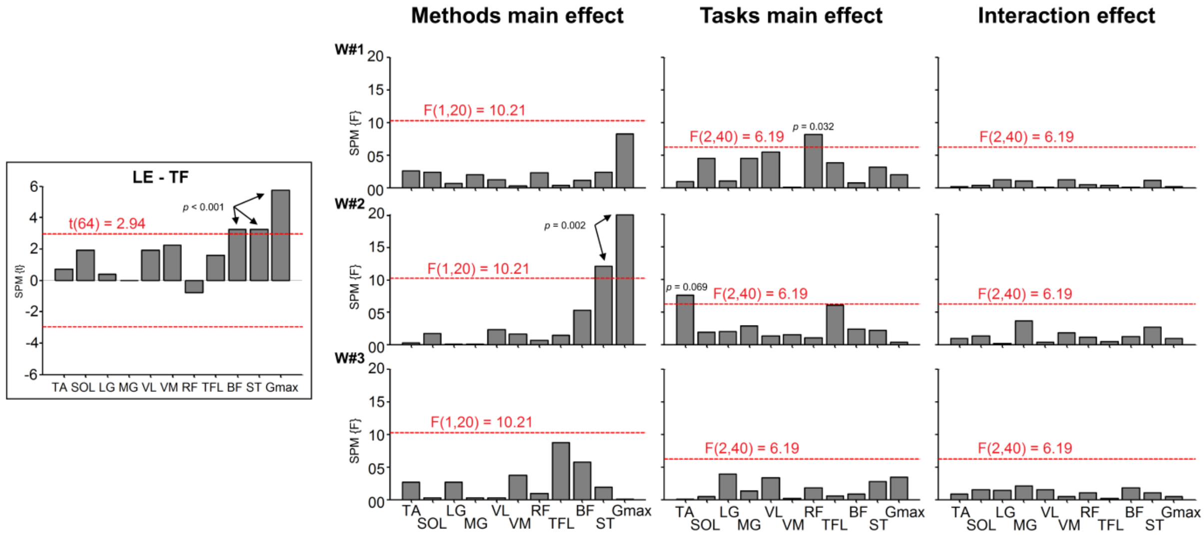

Figure 2: SPM 1D outputs, showing the main effect of extraction methods, pedalling tasks and their interaction on the weightings of the three motor modules (W#1 to W#3). Left inset: *Post-hoc t*-test on the weightings of W#2 between LE and TF methods.

DISCUSSION: Initially, changes were expected in TF muscle synergies according to the different mechanical constraints during the upstroke phase of the pedalling cycle. With regards to this main hypothesis, the results failed to detect any evidence of substantial

changes in the motor module compositions dedicated to the upstroke phase (*i.e.*, **W**#3). Whatever the method of muscle synergies extraction and force produced on the pedal, the results suggested that participants relied on the same motor module, which implied a dorsiflexor muscle (TA) and two hip flexor muscles (RF and TFL).
Relative to the LE muscle synergies, the results agreed with those from Hug et al. (2011) who found similar motor modules compositions and a consistency across different mechanical constraints during pedalling. As the current mechanical constraints differed to those from this previous study, it therefore could be argued that the current data confirmed the robustness of the muscle synergies against mechanical constraints. Such consistency of the motor modules remains one of the main evidences in support of the neural origin of the muscle synergies. As Mornieux et al. (2010) showed an increase in BF activity (+48%) when pulling-up, the nervous system would preferentially increase the muscle activation instead of changing the muscle groupings to produce the adequate output force on the pedal.
The overall similarity with the motor modules obtained with TF methods also could be interpreted as an additional evidence of the motor modularity in the building of motor behaviours by the nervous system. Indeed, our results with the TF approach suggested that muscles of one motor module shared a common neural drive defining the main features in the TF domain of their respective EMG signals. However, a significant reduction in the weighting of the hip extensor muscles (BF, ST and G_{max}) has been detected in **W**#2 when extracted with the TF method in comparison with LE method. Such discrepancy between the methods might suggest that these hip extensor muscles constitute an additional muscle synergy. To check this hypothesis, the TF initial data matrix was reanalysed by extracting 4 TF muscles synergies. In most of the cases (84.8%), two major changes were found: (i) the initial **W**#2 was split into two muscle synergies with the *triceps surae* separated from the hip extensor muscles, while **W**#1 and #3 remained unchanged; (ii) the initial **W**#3 was split into two muscle synergies with ankle dorsiflexor (TA) separated from the hip flexor (RF and TFL) muscles, while **W**#1 and #2 remained unchanged. While the emergence of a new TF muscle synergy had been already reported (Frère, 2017), herein there was any functional (*i.e.*, depending on the task demand) nor individual (*i.e.*, preferred motor strategy) relationship with these two scenarios. Further investigations are thus necessary to better understand the underlying mechanisms of these TF muscle synergies.

CONCLUSION: This study confirmed the consistency of the muscle synergies across different mechanical constraints, even when considering the spectral properties of the EMG signal. The main results support the motor modularity as a neural strategy in the building of motor behaviours.

REFERENCES

Andersson, C.A. & Bro, R. (2000). The N-way toolbox for MATLAB. *Chemometrics and Intelligent Laboratory Systems*, 52, 1-4.
Frère, J. (2017). Spectral properties of multiple myoelectric signals: New insights into the neural origin of muscle synergies. *Neuroscience*, 355, 22-35.
Hermens, H.J., Freriks, B., Disselhorst-Klug, C. & Rau, G. (2000). Development of recommendations for SEMG sensors and sensor placement procedures. *Journal of Electromyography and Kinesiology*, 10, 361–374.
Hug, F., Turpin, N.A., Couturier, A. & Dorel, S. (2011). Consistency of muscle synergies during pedaling across different mechanical constraints. *Journal of Neurophysiology*, 106, 91-103.
Lee, D.D. & Seung, H.S. (2001). Algorithms for non-negative matrix factorization. In *Advances in Neural Information Processing Systems* (pp 556-562).
Mornieux, G., Gollhofer, A. & Stapelfeldt, B. (2010). Muscle coordination while pulling up during cycling. *International Journal of Sports Medicine*, 31, 843-846.
Pataky, T.C. (2012). One-dimensional statistical parametric mapping in Python. *Computer Methods in Biomechanics and Biomedical Engineering*, 15, 295-301.
von Tscharner, V. (2000). Intensity analysis in time-frequency space of surface myoelectric signals by wavelets of specified resolution. *Journal of Electromyography and Kinesiology*, 10, 433-445.

ACKNOWLEDGEMENTS: The authors would like thank Simon Geoffroy and participants for their involvement and the *Université de Lorraine* (FR) for grant support of this study.