

## How do muscles contribute to cycling?

DANIELE BIBBO, SILVIA CONFORTO, CLAUDIO GALLOZZI\*, TOMMASO D'ALESSIO

Dipartimento di Elettronica Applicata - Università degli Studi Roma Tre

Via della Vasca Navale, 84 00146 Roma Italy

\*Istituto di Scienza dello Sport – CONI

Via dei Campi Sportivi 46 - 00197 Roma, Italy

<http://www.dea.uniroma3.it/biolab>

**Abstract:** - Quantitative assessment of muscular activity during cycling could improve the understanding of the occurrence and alternance of muscular synergies during prolonged exercise. A good comprehension of the functional behavior of either single or cooperating muscles, and the analysis of their relation with the force exerted during pedaling, allow the evaluation of the athletes' performance. The purpose of this study was to use a modeling approach in order to predict muscle force patterns during cycling and to compare the predictions with surface ElectroMyoGraphy (sEMG) activity. The model is based on kinematic and dynamic data, acquired during cycling tests by using an instrumented pedal, and on the inverse dynamic analysis. Together with biomechanical data, sEMG signals from rectus femoris, biceps femoris, tibialis anterior and soleus of the dominant leg were acquired. These signals were accurately processed by using an adaptive real-time monitor of myoelectric activity for dynamic protocols in order to estimate the sEMG envelope. The muscular activity provided by both the model and the sEMG envelope has been estimated along the whole test session, and the results have been compared showing a good correlation between the force behavior and the envelope of sEMG signals.

**Key-Words:** - Biomechanics, surface ElectroMyoGraphy (sEMG), muscular activity, cycling.

### 1 Introduction

The quantitative assessment of muscular activity helps in describing the muscular synergies underlying motor tasks execution through time. A thorough understanding of these synergies correspondingly implies the analysis and the comprehension of the relationships between muscular activity, provided by proper processing of surface ElectroMyoGraphy (sEMG) signals, and biomechanics of cycling, i.e. kinematic and dynamic variables.

In the literature there are many studies that evaluate the relationship between sEMG and force exerted, finding a good correlation in static conditions [1]. However, it is generally claimed that this correlation is much more difficult to be established in dynamic conditions, thus preventing a correct assessment of the force contribution of single muscles to the global movement. Therefore the need for studies on the relationship between sEMG and muscular force is to be stressed.

The present work is intended to deal with this problem, as a part of a wider project aiming at the study of athletes' performance during cycling. In a previous work [2] the authors examined muscular activity

of rectus femoris during cycling, and showed how using a pair of electrical indicators, such as mean frequency and amplitude of sEMG signal, it is possible to monitor the instantaneous muscular status in real-time by considering simultaneously fatigue and force production conditions. Special attention has been devoted to the algorithms used to estimate the electrical indicators [3,4], expressly designed to work adaptively according to the statistical characteristics of the signals. The proposed monitor can work in real time in order to prevent muscle failure due to fatigue, thus allowing motor activity to be continued. Applications in sport, for the analysis of performance and the improvement of training procedure, should benefit from this approach.

The effective application of the monitor to cycling needs further improvements such as the integrated analysis of several muscles in order to put in evidence the muscular synergies involved in exercise execution; the measurement of the exerted force in order to predict the muscular force patterns by using an inverse dynamic approach.

Several studies defined muscular synergies by examining either the correlation between muscular activation patterns of pairs of muscles at a given time [5,6]

or the order of recruitment within a muscle group [7]. In this sense the synergies were defined and then identified by the correlated changes in certain performance variables: kinematic, dynamic or electromyographic [8].

More recently, muscular synergies have been defined operationally and from the point of view of motor control as a task-specific group of muscles that stabilizes particular performance variables [9]. It is therefore interesting to identify them as activity patterns of muscles involved in the movement that can change for both biomechanical (e.g. cadence change during pedaling) and physiological modifications (e.g. muscular fatigue).

The sport performance can be improved by learning the proper muscular synergies. In cycling, the task effectiveness can be evaluated from either a bio-energetic or a biomechanical (i.e. measurement of force applied on the pedal and estimation of the kinematics) [10,11] point of view. Neglecting the bio-energetic interpretation, a good performance is characterized by high values of the effective force exerted on the pedal for a portion of the pedaling cycle. The performance can be modified by several factors (i.e. kinematics, dynamic, physiological): position of the foot on the pedal [10], application of a different force profile driven by different patterns of muscular activity, muscular fatigue [11].

An inverse dynamics approach [12] can be used to predict the patterns of muscular force starting from the measurement of the force exerted on the pedal to be correlated with muscle activity through the comparison of the predicted force pattern to the sEMG signal envelope.

Several studies on muscular force prediction presented in the literature [13] neglect the time-varying nature of cycling and consider the exercise as a static task. As a result, they provide single patterns of predicted muscular force and single sEMG envelope obtained by using rectification and low-pass filtering with fixed cut-off frequency. In that way, every modification due to changes in kinematics, dynamics or physiology cannot be considered, and the muscular synergies are difficult to be interpreted.

To overcome this drawback, our work deals with the study of the contribution of lower limb muscles to cycling with particular attention to the changes in muscular synergies due to kinematic, kinetic and physiological modifications. The study will be carried on by implementing a classical inverse dynamics approach to estimate muscular force to be correlated with the electrical indicators of muscular status. In conclusion, the authors will try to give an answer to the question in the title by using quantitative results, thus providing insights on the possibility of using surface electromyography for the assess-

ment of muscular contributions to motor tasks.

## 2 Materials and Methods

This section will be divided into three main subsections respectively devoted to the biomechanical modeling, the experimental set-up and the signal processing.

### 2.1 The biomechanical model

The biomechanical model used for the evaluation of muscular forces was built in three steps:

- definition of a kinematic model to evaluate the position of every segment of the leg involved in the gesture;
- definition of a model based on inverse dynamics approach to evaluate the muscular torque for every joint;
- calculation of muscular forces through the data obtained in the two previous steps.

Using an optimization algorithm, a cost function based on a physiological criterion was minimized to predict muscular force patterns.

#### 2.1.1 The kinematic model

The kinematic model of the lower limb is composed by constrained rigid elements and mechanical elements of the bicycle, used to transmit the motion to the wheel. By modeling each body segment and each mechanical element as a segment (Fig. 1) it is possible to define a kinematic chain composed by the thigh (segment DE), the shank (segment CD), the foot-pedal (segment BC), the crank (segment AB) and the cycle-frame.

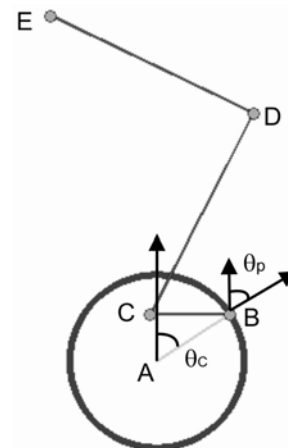


Fig.1: Kinematic chain of the lower limb during pedaling.

The pelvis (point E) was assumed to be fixed to the bicycle frame (point A). In the sagittal plane, the kinematic chain defines a hinge joint model where the trunk is fixed to the frame and the center of rotation of the thigh segment is on the seat.

The foot and the pedal can be considered as a single element because they are fixed with a clipless pedal system. The center of rotation of the crank is fixed on the bicycle frame so that the whole system represents a closed kinematic chain.

This kind of model has 2 d.o.f. so that the position of each member in the sagittal plane can be determined by the length of the corresponding segment together with the relative rotational angle between the frame of the bicycle and the crank,  $\theta_c$ , and the relative rotational angle between the crank and the pedal,  $\theta_p$ . The length of each segment of the model was determined by measuring directly the body segments, the length of the crank, and the distance between the center of rotation of the crank and the seat.

### 2.1.2 The Dynamic model

The kinematic data obtained in the previous analysis and the forces exerted on the pedal (measured as explained in the following paragraph 2.2) were used in an inverse dynamic analysis to obtain the joint moments at ankle, knee and hip. In particular, a free body diagram approach was used. The moment of inertia, the location of the center of mass and the mass of each segment, needed for the calculations of the joint moments, were estimated from height and mass of the athletes by using equations defined in the literature [14].

### 2.1.3 The muscle model

The muscular model considers nine muscles of the leg: tibialis anterior (TA, ankle flexor), soleus (SO, ankle extensor), gastrocnemius (GA, ankle extensor, knee flexor), vastii (VA, knee extensor), rectus femoris (RF, knee extensor, hip flexor), short head of biceps femoris (BFs, knee flexor), long head of biceps femoris (BF, knee flexor, hip extensor), iliacus (IL, hip flexor), and gluteus maximum (GLM, hip extensor).

The number of equations is not sufficient to calculate muscular force values. However, the number of muscles cannot be reduced because they are all needed to describe the biomechanics of the gesture. By considering the gesture as a sequence of simple motor tasks, each muscle in the model is responsible for a single motor task. In the real gesture, this motor task is performed by several muscles, called synergists, that are all represented by the "equivalent" muscle of the model. The reason is that all synergists for the respective "equivalent" muscle of the model have the same activation patterns in cycling as reported in the literature [12]. The relation between muscular moments and muscular forces for every joint considered in the model is given by the equation:

$$\sum F_i \cdot d_{ij} = M_j \quad (2)$$

where  $M_j$  represents the muscular moment for the  $j$ -th joint,  $F_i$  is the force exerted by the  $i$ -th muscle and  $d_{ij}$  is the effective moment arm of the  $i$ -th muscle from the  $j$ -th joint. The values of muscular moment arms were calculated as a function of the joint angle on the basis of the equations in [13].

The muscular forces implied were calculated by minimizing the cost function (3), with the equality constraints given by the equation (2) and with the inequality constraints given in (4):

$$U = \sum_{i=1}^9 \left( \frac{F_i}{PCSA_i} \right)^3 \quad (3)$$

$$0 < F_i < F_{iMAX} \quad (4)$$

where  $F_i$  is the unknown force of the  $i$ -th muscle,  $PCSA_i$  is the physiological cross sectional area of the  $i$ -th muscle,  $F_{iMAX}$  is the maximum force of the  $i$ -th muscle, and  $M_j$  and  $d_{ij}$  have yet been defined.

The cost function was chosen from the literature [15] as the one that best predicts muscular forces considering co-activation of all the muscles involved in the gesture. The cubic exponent used in eq. (3) is based on the relationship between the endurance and the force of the muscles and depends on the specific subject. It guarantees the best tradeoff between the muscular contractile force and the maximum duration of the contraction.

The optimization problem was solved by a routine for the minimization of constrained functions present in the Optimization ToolBox of MATLAB (@The Mathworks, Inc.). Muscular forces were estimated on the basis of the signals acquired in the experimental tests.

## 2.2 Experimental setup

The experimental protocol consisted of pedaling on a cycling simulator for sessions about 50 minutes long. The pedaling cadence was fixed at 70 rpm. The session ended by a sprint followed by a recovery phase. The cycling simulator is equipped with an aerodynamic brake at the wheel, in order to provide a linear relationship between the pedaling frequency and the resistance offered during exercise.

Acquisition of sEMG signals from RF, BF, TA and SO of the dominant leg was carried on by using circular sEMG electrodes (6 mm diameter and 20 mm electrode spacing, center-to-center) and double differential probes.

Simultaneous acquisition of dynamic data was allowed by a laboratory-made instrumented pedal [16] designed to be compliant with a commercial pedal

(i.e. Shimano Pedaling Dynamics SPD™ cleats) and mounted on the cycling simulator. The strain gauge based load cells mounted on the pedal allow the measurement of force components exerted on the pedal. Moreover the angular displacement of the pedal,  $\theta_p$ , was measured by a linear smart encoder placed between the pedal frame and the pedal spindle, while the angular displacement of the crank,  $\theta_c$ , was measured by an encoder that uses the bicycle transmission gear.

Mechanical and sEMG signals were recorded by a movement analysis system (StepPC©, DEM-Italy) with a 2000 samples/s sampling rate and 12 bit A/D converter.

### 2.3 Signal Processing

Recorded signals were processed for different phases of the training session. In particular, the following five one minute long different phases, were considered: the warm-up, two standard situations respectively after 10 and 20 minutes of exercise, the sprint phase, the final phase.

sEMG signals were processed in order to obtain envelope and mean spectral frequency, by means of adaptive and automatic algorithms, already developed by some of the authors. In particular, for each h-th sEMG signal sample, the amplitude  $a(h)$  and the mean frequency  $f(h)$  have been calculated:

- $a(h)$  has been obtained as in [17] by rectification and low-pass filtering of the signal, with adaptive filter length determined as proposed in [18,19];
- $f(h)$  has been calculated as in [4] by iteratively estimating the complex covariance function on a moving window, which for this study has been set at 2 seconds. The window length has been chosen as the best tradeoff between time resolution and variance of estimation.

The mean pedaling cycle for each phase has been considered in order to obtain the mean amplitude envelope of sEMG signal and to compare it to the force profile obtained by the biomechanical model. At the same time, the mean value of the mean frequency has been calculated for each phase of the training session. This value, together with the one related to the signal amplitude, has been used to code the muscular status as in [2], as follows:

- the simultaneous increase of both amplitude and mean spectral frequency is coded as a force increase;
- the simultaneous decrease of both amplitude and mean frequency is coded as a force decrease;
- the increase of the amplitude and the decrease of the mean frequency is coded as muscular fatigue;
- the increase of the mean frequency and the decrease of the amplitude is coded as recovery.

### 3 Results and discussion

Results are provided for a single experimental case in order to show the feasibility of the approach. Statistical purposes are outside the scope of this work.

In Fig. 2 a sample of recorded signals is provided for the warm-up phase of the training session. The sEMG signals of RF, BF, TA and SO are drawn together with the two components of the force exerted on the pedal and the two angles  $\theta_p$  and  $\theta_c$ . In Fig. 3 a sample (5 s) of muscular forces estimated by the model is provided for the same phase as in Fig. 2.

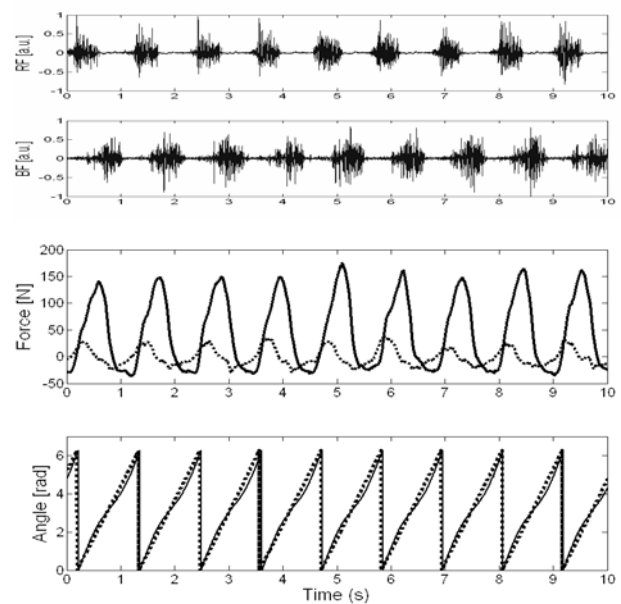


Fig.2: Signals recorded during the warm-up phase of the training session: from the top, normalized raw sEMG of RF, BF vertical (solid line) and horizontal (dotted line) pedal force components, crank angle  $\theta_c$  (dotted line) and pedal angle  $\theta_p$  (solid line).

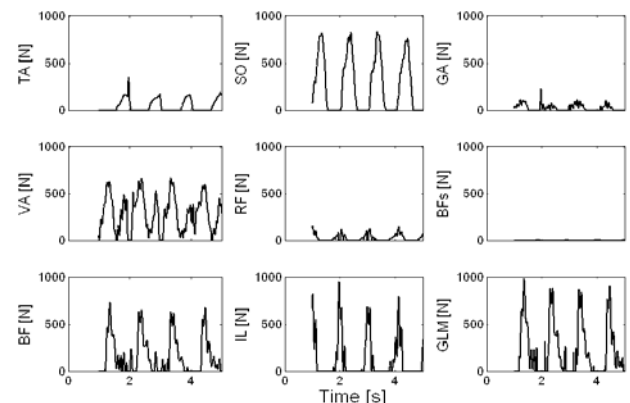


Fig.3: Muscular forces estimated by the model for the nine muscles.

From now on the results will be presented for BF and RF muscles.

In Fig. 4, the force profiles provided by the biomechanical model and the corresponding mean envelopes of sEMG signals for the BF are presented with

reference to the five exercise phases described in the previous paragraph. Trends are drawn with respect to a normalized pedaling cycle and the amplitude values are normalized to the greatest value occurring during the 4-th phase. Since BF and RF activate in an antagonistic way, the choice of a single reference cycle would hinder the visualization of one of the profiles (on the same cycle BF presents the maximum activation about at the 40% while RF presents its activation pattern across the 0% of the cycle). Fig.5 reports the two reference systems chosen to describe the pedaling cycle of the BF and RF muscles respectively.

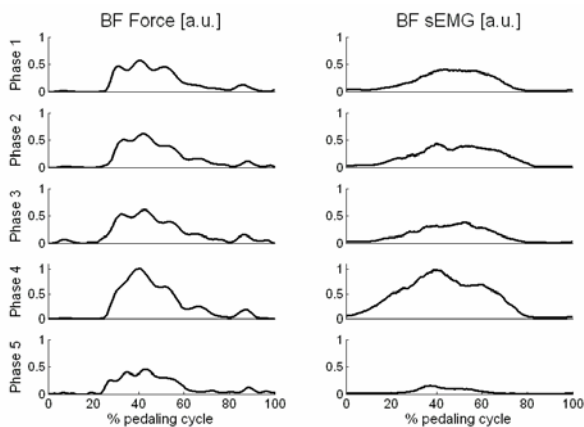


Fig. 4: Forcing profiles and sEMG envelopes for the BF muscle.

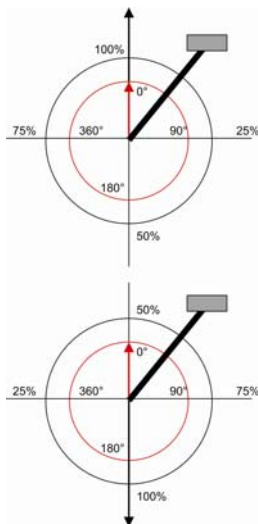


Fig. 5: Reference systems for pedaling cycle: BF (top) and RF (bottom).

In Fig. 6 the force profiles provided by the biomechanical model and the corresponding mean envelopes of sEMG signals for the RF muscle are presented with reference to the five exercise phases, as in Fig.4, while in Table 1, the mean values of the force profiles are provided.

The mean envelopes of sEMG compared to the muscular force profiles show a good agreement with reference to the modifications in the amplitude occurring in the different exercise phases. The values of

the mean frequency and the mean values of the sEMG amplitude envelopes are provided in Table 2.

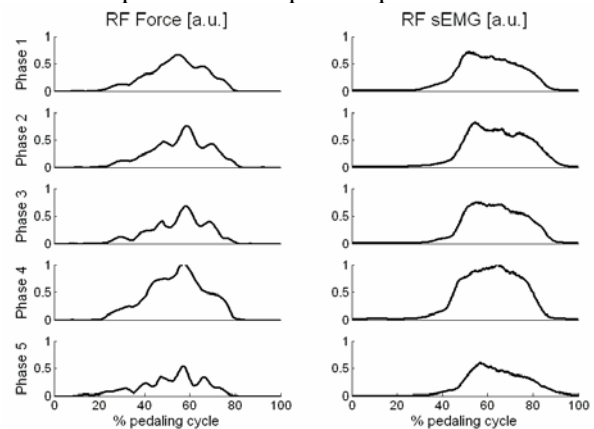


Fig. 6: Force profiles and sEMG envelopes for the RF muscle.

Muscular force (N)		
	RF	BF
Phase 1	32.4	139.0
Phase 2	32.0	140.5
Phase 3	26.6	159.0
Phase 4	49.7	225.5
Phase 5	21.4	112.5

Table 1 – Mean values of the muscular force for RF and BF muscles obtained by the biomechanical model, for the different phases of the training session. Values are expressed in newton.

	Muscular Activity			
	Mean Frequency (Hz)		Amplitude (A.U.)	
	RF	BF	RF	BF
Phase 1	83.3	80.6	0.7	0.4
Phase 2	85.4	85.5	0.8	0.4
Phase 3	83.5	86.5	0.7	0.3
Phase 4	83.3	90.8	1.0	1.0
Phase 5	81.1	80.8	0.5	0.1

Table 2 – Values of the mean power frequency (Hz) and of the mean value of the amplitude for a mean pedaling cycle (Arbitrary Units) for the different phases of the training session.

In order to validate the code of the muscular activity provided by the electrical indicators, the profiles of muscular force estimated by the biomechanical model have to be considered. Looking at Table 2, it is worth to outline how the electrical indicators (i.e. mean frequency and amplitude) code the muscular status, especially for phases 4 and 5 related to sprint and recovery. In phase 4 the muscular code provides a force increase (simultaneous increase of amplitude and mean frequency) for BF, while in phase 5 both muscles can be coded in the force decrease status

(simultaneous decrease of amplitude and mean frequency). This result is confirmed by the muscular forces estimated by the biomechanical model, as it is shown in Fig. 4 and in Table 1 (phase 4 presents the highest force values, phase 5 presents the lowest force values).

#### 4 Conclusions

In this work, a preliminary study on the contribution of lower limb muscles to cycling has been presented, with particular attention to the analysis of changes in muscular synergies due to kinematic, kinetic and physiological modifications. To this purpose a time-varying analysis has been carried on, by analyzing different temporal phases of a training session.

An inverse dynamics approach has been implemented and different patterns of muscular forces have been estimated for all the modeled muscles and for different phases of the cycling exercise. At the same time, sEMG signals have been processed (by using optimized adaptive algorithms) in order to estimate the muscular status and to compare this "electrical estimate" to the muscular forces obtained from the biomechanical model.

Preliminary results show the effectiveness and feasibility of the approach. In particular, the correlation between the force exerted and the sEMG envelope has been put in evidence, together with the substantial agreement of the biomechanical model with the muscular code obtained by electrical indicators estimated from sEMG signals. This conclusion opens a wide field of applications as sEMG signals allow to have information on muscular force and to assess motor performance by means of a non-invasive approach.

Temporal analysis of the force and of the sEMG amplitude profiles appears a valid investigation tool in order to better understand the changes in muscular strategies. However, future work must be directed toward a wide experimental campaign aiming at the statistical validation of the approach which seems very promising.

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