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New approach of cycling phases detection to improve FES-pedaling in SCI individuals

Roberto Baptista^{1,2} *Member, IEEE*, Benot Sijobert¹, Christine Azevedo Coste¹ *Member, IEEE*

Abstract—FES allows spinal cord injured individuals to propel tricycles by means of their own leg power. The stimulation patterns are in most of the cases predefined and muscle activation triggered on the basis of the pedal position. This requires an empirical tuning to fit the pattern to the pilot sitting position and distance to crank with no possible generalization and no adaptive properties. The aim of the present article is to introduce a new approach of motion segmentation based on inertial measurement units located on the cyclist legs with the final aim to predict the optimal pedaling force evolution. Results obtained with one healthy subject in different cycling conditions are presented and the application to FES-cycling discussed.

I. INTRODUCTION

Functional Electrical Stimulation (FES) has been used for decades with cycle ergometers for exercising purposes in lower limb paralysis. Usually, patients are sitting in a wheelchair and their legs are fixed to the pedals using ankle orthoses. Different studies have shown the benefits of this type of training in individuals with complete spinal cord injuries (SCI) to reduce the complications related to the paralysis [1], [2], [3].

Overground cycling using mobile tricycles has also been considered in order to add a recreational aspect to the exercise. Since 2006, different competitions have been proposed in order to promote FES-cycling [4] aiming at improving life quality and self-esteem by giving an active role to paralyzed limbs in a locomotor activity.

In most of the systems, the crank angle is measured through an encoder in order to track the pedaling cycle execution which allows to trigger pre-programmed stimulation sequences over the different muscles [5]. Usually Quadriceps, Hamstrings and Gluteus groups are considered. The different muscle activation phases are associated to the crank angle values. As already discussed in previous articles, the use of the crank angle as the input command to trigger the different muscle stimulation phases has two main disadvantages [6]: the need for a dedicated sensor such as an encoder [7] or an inertial sensor [8] to measure crank angle and the calibration phase to determine the muscle activation pattern for a given sitting position [9]. Some authors have explored the possibility to control muscle activation without defining a desired pattern a priori [10].

Recently, a new method has been proposed for estimating knee and hip cycling percentage (CP) using inertial measurement units (IMU) located on the shanks and thighs of both legs [11], [12]. Using a two-dimensional geometric model for the lower limbs, the knee and hip absolute angles are estimated from the IMUs and then transformed to a normalized range [0;1]. Instead of using the crank angle based stimulation pattern, the CPs are used to define the stimulation pattern for each leg. The CPs defines two zones: flexion / extension of the corresponding joint (knee/hip). Depending on the different phases, different muscle contributions should be activated to produce a positive torque (Rectus femoris, Hamstrings or Bicep Femoris). Knee and hip extension and flexion phases being synergistic only knee CP was used in the end. This allows the authors to define a generic muscle activation pattern which is independent of the sitting position and distance to crank.

For robustness purposes regarding the changes occurring in the absolute joint angle evolution due to sliding on the seat or IMU oscillations, the joint angle is bounded using maximum and minimum peak values. To guarantee a safe switching between phases in cases of disruptions a criterion is introduced as well as an hysteresis between states [11]. An improvement to guarantee a safe switching between the phases for the knee joint criteria is presented in [12] which includes an extra variable, polar coordinates of right and left leg, that are also estimated from IMU readings. The delay between stimulation onset and force production needs to be integrated and speed compensation methods developed as suggested in [13].

In the present article we propose a different approach of segmenting the pedaling cycle in phases based on knee angle measurements using a method adapted from [14], [15]. This method allows a robust segmentation, recognition and assessment of human movements based on Switching Linear Dynamic System (SLDS) modeling. As shown in [14], this SLDS modeling approach is more robust than conventional Finite State Machines (FSM) with fixed guard conditions, particularly for detecting changes in phases for human movement segmentation. Segmenting the pedaling cycle is a particular case for this generic SLDS modeling approach that we intended to explore in the present article. Our goal is to propose an estimation method that allows to correctly classify each phase of the pedaling movement, based only on knee angle measurements and intrinsically ensuring robustness to slight changes in the cycling pattern. A preliminary validation is performed on experimental data from one healthy individual and performances in segmenting

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the pedaling cycle of the method are analyzed.

This paper is organized as follows: Section II introduces the proposed method for cycling phases segmentation, Section III presents the experimental setup used to collect data during cycling trials and describes the datasets used for validation of the segmentation method. Section III-B presents the results obtained and is followed by a general discussion and conclusion.

II. CYCLING PHASES SEGMENTATION ALGORITHM

In a previous article [15], a methodology was proposed to model, segment, recognize and assess human movement using the Switching Linear Dynamic System (SLDS) modeling approach. In the present paper, this approach was adapted to segment a sequence of pedaling cycles in order to detect knee flexion and extension movements. In the following, first the SLDS approach is presented and then an explanation of the proposed approach for cycling is detailed.

In essence, in the context of pedaling, the SLDS model can be seen as an elaborated finite state machine (FSM), in which the estimation of the current state is determined by both the dynamic behaviour of the continuous variables (knee angles) and the interaction among the three phases (still, flexion, extension).

A. Switching Linear Dynamic Systems

A SLDS is a model used to represent complex, non-linear systems through a combination (or switching) of simpler linear state-space models.

It is composed by a conventional state-space model, but indexed by a variable s_t in the form:

$$\begin{aligned} x_{t+1} &= A(s_{t+1})x_t + v_{t+1}(s_{t+1}) \\ y_t &= Cx_t + w_t, \quad \text{with} \\ x_0 &= v_0(s_0) \end{aligned} \quad (1)$$

where $x_t \in \mathfrak{R}^N$ is the hidden state of the state-space model, v_t is the state noise, $y_t \in \mathfrak{R}^M$ is the observed measurement of the system, w_t is the measurement noise. $A(s_t)$ is the state transition matrix and C is the observation matrix.

The switching variable, s_t , belongs to a set of S discrete symbols $\{c_1, \dots, c_S\}$ and its dynamic is modelled similarly to a Hidden Markov Model (HMM):

$$\begin{aligned} Pr(s_{t+1}|s_t) &= s'_{t+1}\Pi s_t, \quad \text{with} \\ Pr(s_0) &= \pi_0 \end{aligned} \quad (2)$$

where the state transition matrix Π , whose elements are $\Pi(i, j) = Pr(s_{t+1} = c_i | s_t = c_j)$, represents the probability of $s_{t+1} = c_i$, given that $s_t = c_j$. The state transition matrix $A(s_t)$ and the measurement noise $v(s_t) \sim N(0, Q(s_t))$ are associated with a switching variable s_t , which indicates which model $(A(s_t), v_t)$ is used at each time t .

Besides the formal modeling, the SLDS approach develops the probabilistic equations for learning the parameters of the models (specially $A(c_S), Q(c_S), \Pi$) and tracking the observed measurements in a time-series (specially s_t, x_t), combining two well known probabilistic approaches: the Kalman Filter

and Hidden Markov models. The method presented in [15] explains how to automatically set the parameters of a SLDS model for human movement using labeled datasets. Furthermore, it explains the estimation algorithms to segment, recognize and assess a sequence of human movements using the parameterized SLDS model.

B. SLDS Model for Cycling

The representation of knee flexion and extension movements is a particular case of the method. Three phases are defined for cycling: the first phase, or still phase corresponds to the situation when the legs are immobile (no variation of knee angles); the second phase corresponds to the right knee extension and left knee flexion situation; and finally the third phase corresponds to the left knee extension and right knee flexion situation. Figure 1 presents the three phases for one complete pedaling cycle, taken as a snippet from one experimental dataset. In this paper we used the time-series for both the right and left knee angle measurements as a two-dimensional array to estimate the three phases. This means that for each phase there is a two-dimensional state-space model as in Eq. 1. The switching variable, s_t , indicates at each sampling time the current phase, which evolves according to Eq. 2. The goal in this case is to estimate the value of s_t at each moment and detect transitions between the three phases.

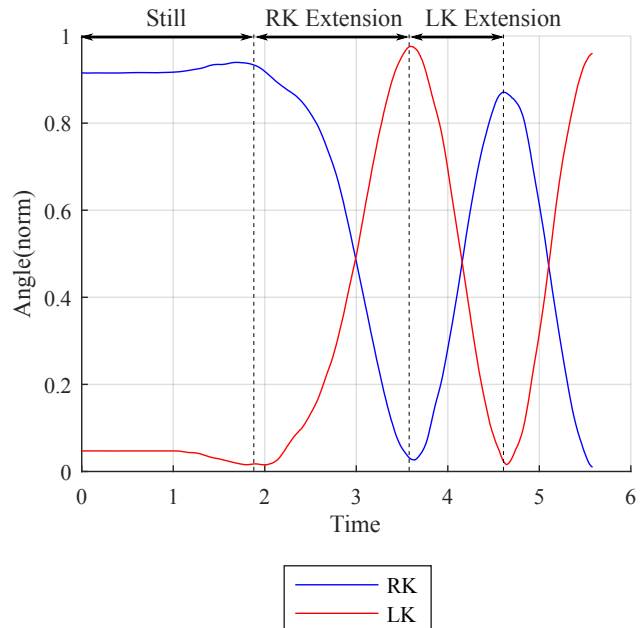


Fig. 1. Segmentation of a sequence representing the three phases of cycling. Depicted are experimental data recorded in one healthy individual over one pedalling cycles starting from a resting position: right knee angle evolution (RK), left knee angle evolution (LK). Each phase is identified and labelled: still, RK extension and LK extension.

There are two main steps in the proposed approach. First a labeled experimental dataset containing at least one interval for each phase is used to automatically extract the parameters for the components of the SLDS model as in Eq. 1 and

2. Later this model is used to estimate the phases at each sample time in an experimental dataset. The estimation is achieved using the Viterbi algorithm adapted to SLDS models introduced in [17].

We previously showed on [15] that once the SLDS model is parameterized, it can be applied to datasets from other trials, also including different subjects. The movements in the trials must be contained in the set of movements of the parameterization dataset. Furthermore, since the SLDS model looks at the overall movement patterns, it is robust against slight deviations on sensor placement and subject's size and body type.

III. EXPERIMENTAL VALIDATION

One healthy subject was installed on a recumbent tricycle ICE Adventure[®]. Slight mechanical adaptations were made to adapt the tricycle for a SCI subject and are described in [7]. Feet were fixed to the pedals by means of calf support holding the ankle joint at 90°.

The subject was equipped with 4 inertial measurement units (IMU Bosch BNO055) on shank and thigh bilaterally (fig.2) to assess knee angles. The IMUs were placed on the shanks and thighs with custom rubber straps. Each sensor embedded a high speed ARM Cortex-M0 based processor to process all the sensor data, abstract the sensor fusion and directly provide a quaternion representation relative to Earth frame, at a sampling rate of 100 Hz. The quaternion expressing the rotation of the shank relative to the thigh was computed via an Hamilton product of the thigh quaternion conjugate in Earth frame by the shank quaternion in Earth frame. Both shank and thigh quaternions in the Earth Frame were estimated by an extended kalman filter fusion sensor algorithm running on each of the BNO055 IMU. Quaternions were then converted to Euler angles in order to compute knee angles. The four IMUs were connected and wired to a Raspberry PI3.

This IMU-based measurement setup was previously validated with an external reference system and provides reliable angle measurements [20].

Two additional wireless IMUs (Hikob FOX, Villeurbanne, France) were located on the crank and rear wheel. Raw inertial data recorded at 20 Hz were used to estimate crank angle, pedalling cadence and trike velocity. Martin et al. [16] fusion sensor algorithm was implemented to be used to compute crank angle, bike velocity was accurately and directly measured from the gyrometer data.

A. Validation dataset

Two trials were executed during which two datasets were collected to showcase our method. The subject was pedalling over a 45 meter straight corridor, starting from a still position and pushed into motion by a helper. In the first experiment, the subject was instructed to keep a constant cadence of 5 km/h with visual and auditory cues from the instrumentation system and the experimenter. For the second experiment, the subject was instructed to vary the cadence along the trajectory: first, to keep a constant cadence lower

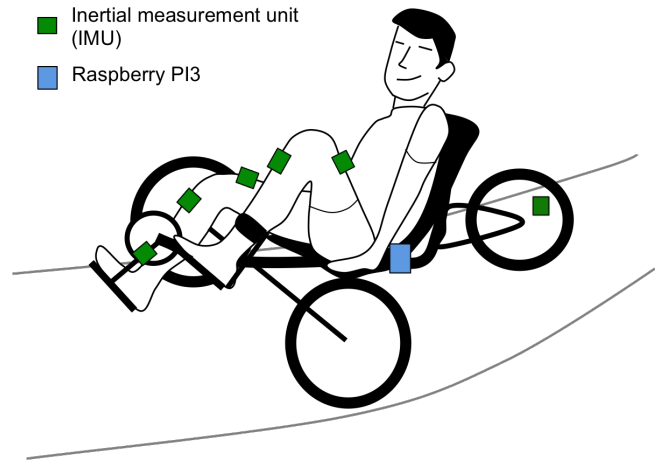


Fig. 2. Schematic view describing the experimental setup used to validate the proposed segmentation approach.

than 5 km/h, then, with an auditory cue, he was instructed to increase the cadence to around 5 km/h in the middle part of the corridor and finally increase the cadence to above 5 km/h towards the end of the trial.

Our method does not assume that the movement is cyclic, so we tested each dataset in two situations: one including the still phase at the beginning (datasets named SCC and SVC) and another situation where we excluded the still phase and starting at the second pedaling cycle (datasets CC and VC).

Given the high sampling rate for the IMUs positioned on the subject's legs, the datasets containing the estimated angles from the IMUs were decimated to a sampling frequency of 50 Hz and all variables were normalized according to the maximum and minimum value for each variable in each dataset. Also, the angle estimations from the IMUs in each dataset were smoothed using a 10 sample fixed window moving average filter. The moving average filter was chosen to reduce noise and keep a sharp step response, i.e. to capture the overall angle movement pattern [21].

Initially, a subset of the SCC dataset including the still stand and two complete pedaling cycles was used to identify the SLDS model's parameter.

Right and left knee estimated angles based on IMUs measurements were manually labeled to indicate each of the following phase: P1) still; P2) right knee extension/left knee flexion and P3) left knee extension/right knee flexion. An automatic parameterization procedure, as described in Section II, processed this labeled dataset and resulted in a parameterized multidimensional SLDS model capturing the dynamics of the knee angles for each phase as well as the transitions between them.

Next, the parameterized SLDS model was used, along with the estimation algorithm, to automatically segment the four datasets (SCC, SVC, CC, VC) into the three distinct phases. The output is a set of labels, which indicate the phase of each data sample. The results are presented in Section III-B.

To assess the results of the estimation algorithm, we used the following statistics: True Positive (TP), False Positive

(FP) and False Negative (FN), expressed as a percentage of the total of true transitions between phases in each dataset. Each dataset was manually labeled to identify the true transitions, which were taken either as peak or valley points representing the knee flexion or extension movements. A TP is an estimation that matches the true transition, a FP is the estimation of a transition, when there is none, and a FN is the miss of a transition in the estimation. Besides checking for the estimation at the correct instant, a tolerance for delay, t_{error} was taken in account, so a correct transition estimate with a delay of less than 60 ms was considered a TP.

B. Results

An overview of the results is depicted in Figure 3. The time-series for the first 25 s of the varied cadence dataset for the following normalized variables are shown: right knee angle, left knee angle and speed, along with the estimated phase classification: still (P1), right knee extension (P2) and left knee extension (P3). Although the pedalling motion is cyclic, it is clear in Figure 3 that peak and valley values are not constant. Furthermore, the period for each cycle varies according to the change in cadence, as expected. Numerical

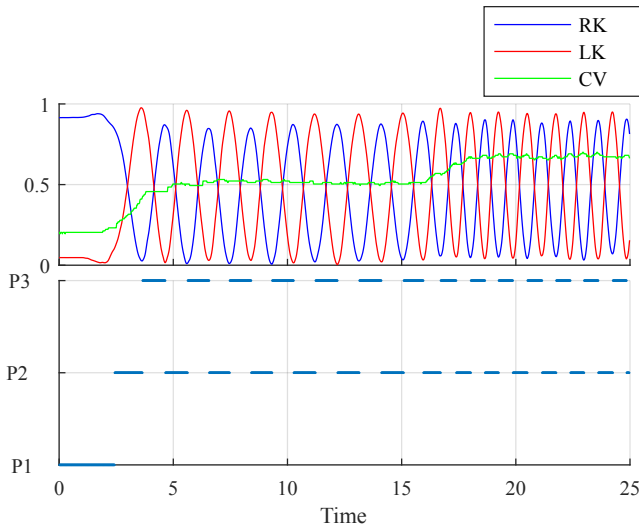


Fig. 3. Results for classification for the first 25 seconds on the varied cadence dataset. Depicted are the normalized data: right knee angle (RK), left knee angle (LK), cycle velocity (CV), and the estimated phases from automatic segmentation algorithm for each data sample: still (P1), right leg extension (P2), left leg extension (P3).

results for segmentation estimation for both datasets are presented in Table I as percentage for the statistics: TP, FN and FP. The fact that in all cases the FP is equal to FN means that the number of estimated transitions matches the number of true transitions, but they were outside the tolerance t_{error} .

Figure 4(a) and 4(b) show an example of a FP and FN compared to the true transition moment.

Although the correct estimation at the true instant, i.e. $t_{error} = 0$ ms is poor in some cases (for the SVC dataset the TP is only 58), in all cases the results improves when taking the tolerance of $t_{error} = 60$ ms. This is the case depicted

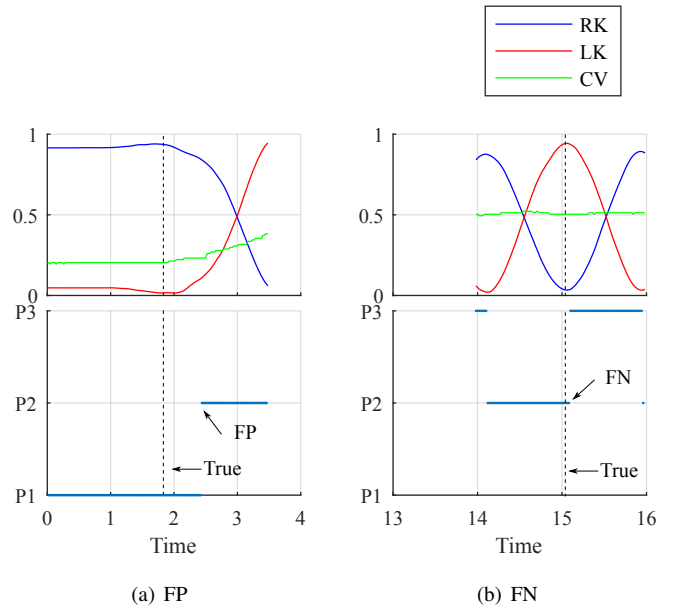


Fig. 4. Example of FP and FN estimation compared to true transition moment

in Figure 4(b). The difference in the performance between both SCC and SVC datasets (TP = 98%) and the CC and VC (TP=100%) is caused by the miss in the estimation of the transition from the still phase to the right knee extension phase (P1 to P2). As illustrated in Figure 3 this transition is indeed estimated in all cases, but far from the $t_{error} = 60$ ms tolerance. In fact, for the SCC dataset the delay for this estimation was 620 ms and for the SVC dataset it was 520 ms. This is the case depicted in Figure 4(a).

TABLE I
SEGMENTATION RESULTS FOR THE CONSTANT AND VARIABLE CADENCE (CC AND VC), AND DATASETS INCLUDING THE INITIAL STILL STAND (SCC AND SVC). RESULT IS PRESENTED AS TRUE POSITIVE (TP), FALSE POSITIVE (FP) AND FALSE NEGATIVE (FN), EXPRESSED AS A PERCENTAGE (%) OF THE TOTAL TRUE TRANSITIONS, WITHIN AN ERROR BOUND (t_{error})

Dataset	$t_{error}=0ms$			$t_{error}<60ms$		
	TP	FP	FN	TP	FP	FN
SCC	98	2	2	98	2	2
SVC	58	41	41	98	2	2
CC	71	29	29	100	0	0
VC	60	40	40	100	0	0

IV. DISCUSSION

The results in Section III-B show that the proposed method is adequate to segment the pedaling cycle considering a small tolerance for delay in the phase transition estimation. This provides a robust approach, regarding changes in cycling pattern due to small IMU placement oscillations, since no special attention was given to precise IMU placement and our previous results [19] confirm that the method works as long as the overall movement pattern is captured. For the datasets which the still position is not included and considering an

error bound of $t_{error} = 60 \text{ ms}$ we achieved a success rate of 100% in phase transition detection. We consider this a suitable result to use as a triggering condition for the FES activation and control scheme.

A direct comparison with the method proposed in [11], [12] is not possible because the authors did not provide performance results for the specific task of segmenting the pedaling cycle. Furthermore, they did not provide sufficient details to allow us to implement their method and make a fair comparison. However, a qualitative comparison is possible.

The main concerns regarding the phase detection algorithm to use in the context of FES activation in cycling are: the correct detection of transition at the moment it occurs, and the avoidance of fast-switching when estimating phase transitions. The method proposed in [11], [12] relies directly on a geometric model of the lower limbs and crank to estimate the transition. Theoretically this would be sufficient to guarantee a correct estimation, but there are shortcomings in this approach. Sliding in seat position and IMU placement and readings oscillations disturbs the output. Some heuristics must be taken to ensure safe switching: including a small hysteresis in the estimation procedure [11] and include an extra guard condition, the polar coordinates of each leg [12]. These are usual adjustments in methods, which are developed for segmenting a specific movement pattern.

In contrast, we used a generic method for human movement segmentation and adapted it to the case of segmenting the pedaling cycle. This approach is straightforward and avoids the use of heuristics. Also no assumption on the cyclic property of the motion is made, a stochastic model is parameterized using only one labeled dataset.

Fast switching can occur, especially when dealing with noisy data. We overcame this by smoothing data with a moving average filter, in fact any low-pass filter could be used. It is important to notice that fast-switching did not occur in our tests in which we used datasets containing variations in both cycle period and min/max values, providing evidence that our method is robust against changes in cycling pattern due for instance to seat sliding or IMU displacements.

Delay in estimation is expected when using stochastic filters, since we make the decision based on the probability that a sample belongs to one or another phase, and its impact is evident in Table I. Considering the datasets containing only movement, all transitions were correctly estimated within 60 ms. In FES activation schemes for cycling, usually a latency time of 130 ms is taken in account for muscle force response [13]. Therefore, we consider 60 ms an acceptable delay. However its impact must be further explored in the complete context of FES triggering and control scheme. The delay in the detection of the transition from still position to right knee extension is high compared to the delay for the other transitions. But from the still position the movement must be started at an arbitrary moment and FES activation usually occurs during movement. The correct detection of still phase could be useful to detect when the movement seized, particularly due to muscle fatigue.

Besides providing an alternative method for pedaling cycle

segmentation for FES triggering, using this type of stochastic filter approach allows to extend the method to include other functionalities. One possible development is to forecast the switching moment, which can be used to anticipate the trigger of the FES to accommodate the latency for muscle response. Another possibility is to track the knee angle at the transitions and use this measurement to detect changes in the subject's posture due for instance to sliding on the seat. Finally, the next step of this work will be to test this estimation with a FES trigger and control scheme.

V. CONCLUSION

A new approach to segment pedaling cycle based on knee joint angles was proposed. In contrast to previous approaches developed specifically for this purpose and which require some heuristics to guarantee robustness, our approach is based on a generic method for human movement segmentation and is modeled using experimental labeled datasets. Results show that this method is robust to fast-switching between transitions and correctly estimates the transitions between knee flexion and extension movements. Furthermore, since no assumption of cyclic motion is made, a stand still phase can also be included in the model. Our method is based on stochastic filters and provides estimates on discrete and continuous variables and could be used to forecast transitions or assess the quality of the motion. The direct application of this approach will be to include this estimation procedure in a scheme for trigger and control of FES cycling in order to activate the different muscles at the correct instant to propel a tricycle.

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