# Characterizing Parkinson's desease using EMG fractional linear prediction

Philippe RAVIER[1], Meryem JABLOUN[1], Mohamed Lamine TALBI[2], Ross PARRY[3], Elodie LALO[3], Olivier BUTTELLI[1]

[1]PRISME laboratory
University of Orléans,
France

[2]ETA laboratory,
University of Bordj Bou Arréridj,
Algeria

[3]ICM Institute, CNRS, INSERM,
University of Paris 6,
France

***Abstract*—In this paper, we propose a modeling technique for the surface electromyographic (sEMG) signals based on the fractional linear prediction (FLP). To our knowledge, this is the first time application (use) of the FLP modeling to sEMG Data. This study is motivated by the ability of FLP modeling for characterizing a waveform with a reduced set of parameters. The FLP is applied on real sEMG data recorded on the *Soleus* muscles under walking conditions and preliminary results are obtained. The dynamics of FLP coefficients for persons suffering from Parkinson's disease (PD) were shown to be lower than those for healthy subjects. This suggests less adjustment possibilities in the neuromuscular response of the PD subjects compared to the healthy subjects. Perspectives are the evaluation of fractal components of nonstationary EMG data in connection with FLP evolution.**

***Keywords-component; EMG; Fractional linear prediction FLP modeling; Parkinson's desease.***

## I. INTRODUCTION

Modeling is a mathematical representation useful for expressing in a more simple way the complexity of phenomena and helps understanding them. In the data processing domain, the importance of modeling is critical in many applications, like noise removal, signal compression or features extraction, since the final quality of the processing is dependent of the information which is caught by the model. Many ways for building appropriate models are possible: local and fine analysis of the data generating processes which requires some understanding and assumptions of phenomena; global or coarse analysis of the data reflecting mean behaviors of the phenomena. When scientific knowledge for building a model following the first way is deficient, the second way may be adopted. The interest of the second way lies on the possible interpretation and understanding of phenomena based on previous studies having shown the ability of the model to catch some specific information in the data. The proposed study falls in this scope with the modeling and analysis of surface electromyography (sEMG) data recorded on the *Soleus* muscles of persons suffering from Parkinson's disease (PD). Even if many models have been previously proposed for healthy EMG signals, they cannot directly be transposed to the PD case in particular because motor unit recruitment strategies which drive muscle contractions are not known. In order to circumvent the lack of knowledge for a fine sEMG modeling in the case of PD, we propose to use the fractional linear prediction (FLP) modeling which has shown to be a shape descriptor of data suitable for classification purpose [1]. In opposite to random process models like autoregressive (AR) models, which assume stationary random data [2], FLP modeling is a deterministic process based on a recurrent definition of data expressed as a linear combination of fractional integrals or derivatives of the signal at different non integer orders [3].

Various engineering science problems has found interest in fractional calculus. For example, fractional calculus was useful in automatics for designing robust command [4].

Recent studies in physiological signal modeling have employed the FLP to model speech [5], EEG signal [3][6] and recently ECG [1]. Motivated by the effectiveness of the FLP method for physiological applications, we propose in this work to investigate for the first time the potential of this technique as a new tool for efficiently modeling sEMG signals. The main objective is to evaluate the ability of FLP modeling in characterizing Parkinson's disease by studying variations of FLP coefficients of sEMG signals during walking situations.

## II. THE FRACTIONAL CALCULUS

### A. General concepts

Fractional calculus can be considered as an extension and generalization to fractional order of the integer order calculus, both for derivation and integration operations. Its definition is not straightforward and one of the most accepted definition is the Grünwald-Letnikov formulation which is the expansion of successive interlocked derivations starting from the original

978-0-9928-6265-7/16/$31.00 ©2016 IEEE

derivation formula [3]. This strategy produces the following expression:

$$ {}_aD_t^{\alpha} f(t) = \lim_{h \to 0} \frac{1}{h^{\alpha}} \sum_{j=0}^{\left[\frac{t-a}{h}\right]} (-1)^j \binom{\alpha}{j} f(t - jh) \quad (1) $$

where the combinational $\binom{\alpha}{j}$ can easily be defined with fractional order $\alpha$ instead of an integer order:

$$ \binom{\alpha}{j} = \begin{cases} 1 & \text{for } j = 0 \\ \dfrac{\alpha(\alpha-1)\ldots.(\alpha-j+1)}{j!} & \text{for } j = 1,2,3 \ldots \end{cases} \quad (2) $$

${}_aD_t^{\alpha} f(t)$ denotes fractional-order differintegrals operator of order $\alpha$ applied on the continuous function $f(t)$. In the digital domain, a simplified version of the fractional-order differintegrals operator can be obtained using a direct discretization of the previous equation:

$$ D^{\alpha} f(n) = \sum_{j=0}^{n} (-1)^j \binom{\alpha}{j} f(n-j) \quad (3) $$

This expression can be retrieved considering the first-order backwards finite difference of a derivative which can be developed using a Mac Laurin expansion. Indeed, in the Laplace domain, the derivative of order $\alpha$ of any function $f(t)$ implies the multiplication of its Laplace transform with $s^{\alpha}$, with $s$ being the Laplace variable (used for continuous time functions). Considering the first-order backwards finite difference method which transforms $\frac{df(t)}{dt}$ to $f(n) - f(n-1)$ and using the variable $z$ appropriate for $T$-sampled discrete time functions, we obtain:

$$ s^{\alpha} = \left(\frac{1 - z^{-1}}{T}\right)^{\alpha} = \frac{\sum_{j=0}^{+\infty} (-1)^j \binom{\alpha}{j} z^j}{T^{\alpha}} \quad (4) $$

However, the Mac Laurin power expansion has to be truncated to the $n$ number of available samples instead of the infinite number of samples mentioned in the formula. Thus the truncation of the sum makes the discrete derivative version approximate:

$$ \left(\frac{1 - z^{-1}}{T}\right)^{\alpha} \approx \frac{\sum_{j=0}^{n} (-1)^j \binom{\alpha}{j} z^j}{T^{\alpha}} \quad (5) $$

Nevertheless, the error rapidly becomes negligible when time $n$ increases because the combinatorial gives weight to the most recent samples only, which are thus truncated at the beginning of the computation (first derivative samples computed). Finally, the fractional derivation of order $\alpha$ of a function $f(n)$ can be achieved by a digital linear filter which coefficients are those of the power series expansion.

The fractional operator can therefore be characterized by a linear filter but with limited number of coefficients.

For sake of reproducibility, we have used the Ninteger toolbox [7] to calculate the fractional-order derivation / integration. In this work, the fractional-order operator has been approximated to the order 6 of the Mac Laurin series expansion, because higher order terms have negligible contribution. The used filter expressions are given in [1].

### *B. Fractional linear prediction (FLP) modeling*

The FLP modeling of a signal $x(n)$ can be expressed as the prediction $\hat{x}(n)$ of $x(n)$ when expanded as a linear combination of its fractional derivatives or integrals.
Using fractional derivative operators, the prediction writes

$$ \hat{x}(n) = \sum_{i=1}^{Q} \alpha_i D^{p_i} x(n), \quad (6) $$

where $p_i > 0$ and $D^{p_i}$ denotes the fractional derivative operator with fractional order value $p_i$. The $\alpha_i$ values are the FLP coefficients, the number of which is $Q$ referred to the FLP model order. When $p_i < 0$, $D^{p_i}$ becomes a fractional integral operator and the FLP coefficients are named $\beta_i$ in eq. (6) which gives the following prediction equation

$$ \hat{x}(n) = \sum_{i=1}^{Q} \beta_i D^{p_i} x(n). \quad (7) $$

Now, the way to compute the coefficients is similar to the AR modeling resolution. The estimation of the vector parameter $\boldsymbol{\beta} = [\beta_1, \beta_2, \ldots\ldots\ldots, \beta_Q]^T$ is achieved by minimizing the energy of the prediction error $w(n)$ between $\hat{x}(n)$ and $x(n)$. The $N$ data samples can be stacked in a vector $\boldsymbol{x}$ on which the integral operator of order $p_i$ can be applied $Q$ times as $\boldsymbol{\rho_{p_i}} = D^{p_i}\boldsymbol{x}$ producing a matrix $\boldsymbol{H} = \left[\boldsymbol{\rho_{p_1}}, \boldsymbol{\rho_{p_2}}, \ldots\ldots\ldots, \boldsymbol{\rho_{p_Q}}\right]$. The prediction errors can also be put in a vector $\boldsymbol{w}$. Finally, the problem is reduced to the equation $\boldsymbol{x} = \boldsymbol{H\beta} + \boldsymbol{w}$ that is solved by least squares estimation procedure giving the estimated FLP coefficients $\widehat{\boldsymbol{\beta}}$ as:

$$ \widehat{\boldsymbol{\beta}} = (\boldsymbol{H^T H})^{-1} \boldsymbol{H^T x} \quad (8) $$

## III. RESULTS AND DISCUSSION

### *A. sEMG acquisition protocol*

The sEMG data were acquired in the frame of the EcoTech project aiming at characterizing gait troubles of subjects suffering from Parkinson's disease. We have analyzed 12 subjects having given consent for participating to this study, composed of 6 healthy persons and 6 persons suffering from Parkinson's disease with different levels of gravity. The sEMG activity were acquired at the same time on different muscles and we focused on the *Soleus* muscle at the left leg and at the right leg because this muscle controls the ankle plantar flexion (agonist) and consequently it is involved in the gait activities.

The experiments have been conducted with wireless wearable sensor units from TEA Company, France. The skin was shaved and cleaned. The sEMG activities were acquired by means of electrodes appropriately located on the *Soleus* muscles at a sampling rate of 1926 samples / sec with 16 bits. The length of the acquired data could strongly vary between the subjects and the experiments because of possible different protocols between subjects (with or without medication in the Parkinson's disease case) and because of the difficulty encountered in collecting data in ecological walking situations without any instructions.

Illustrative examples of typical recorded series of sEMG burst for healthy and PD subjects during walking are given in fig. 1.

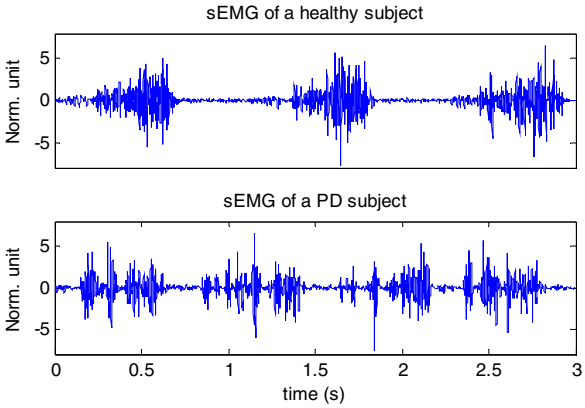


Figure 1 Examples of sEMG recordings for the left Soleus of a healthy subject and a PD subject. The subjects were walking without any instruction.

## B. *Dynamics of FLP sEMG data processing*

We are interested in studying the evolution of the changes along the time of the $\beta_i$ FLP modeling coefficients. Like for random process models, the issue for the number Q of coefficients arises. In the case of FLP modeling, the choice of the integration orders is also an open issue. Nevertheless, previous studies demonstrated that a number of 3 parameters was sufficient, a higher number producing too low value coefficients. The parameter orders were fixed to $\{p_1, p_2, p_3\} = \{-0.15, -0.3, -0.45\}$.

The sEMG data were 500ms sliced processed with a Hanning weighting window being applied on each slice. For each slice, the set of $\{\beta_1, \beta_2, \beta_3\}$ FLP coefficient values were obtained as sEMG model parameters. The dynamics of the model parameters were evaluated using the standard deviation (STD) of the parameter sequence, either globally or locally along the experimental phases for specific subjects.

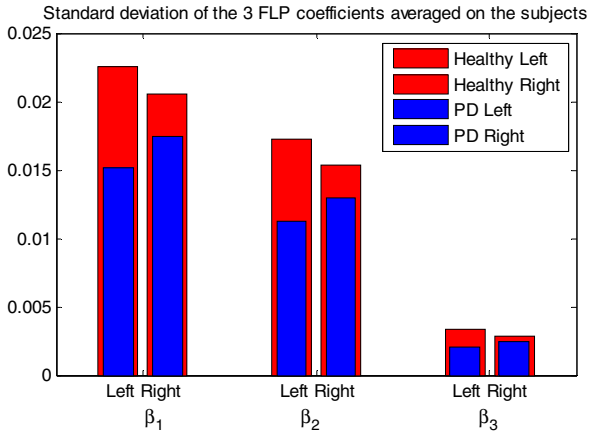


Figure 2. Standard variation of the three FLP coefficients computed on 500 ms successive temporal sEMG weighted windows. The data were acquired on the left and right *Soleus* during walking situations for healthy persons and for PD patients. Averaged values are reported.

Fig. 2 shows the averaged value on all subjects of the STD statistic computed for the three model parameters. Results were obtained for the healthy population *vs* PD population, both for the left leg and the right leg. The three parameters showed less variability in the PD case compared to the healthy case, whatever the leg.

Fig. 3, fig. 4 and fig. 5 show the evolution along the time of instantaneous STD values. These values are computed at each slice instant (time resolution of 500 ms) from the ten preceding values of the parameter $\beta_i$, for each i. For the two PD considered cases, an increase of all the STD values can be observed from the middle of the experiment to the end.

## C. *Discussion*

Surface electromyography activity (sEMG) is a useful means for studying the neural drive modifications during motor activity [8]. So the interpretation of the sEMG FLP modeling modifications may help studying neural drive strategies during motor activities.

In the case of the Parkinson's disease, a major element for the therapy adjustment lies in the motor function fluctuations along the day, in particular in connection with the medication dates. The examples of fig. 4 and 5 for a PD subject illustrate this fluctuation which is observed during walking situation, when the sEMG activity is measured on the *Soleus* muscle, as a function of the date after medication (the first point corresponds to the date of the medication). The activity of the *Soleus* muscle for a healthy subject is also reported on fig. 3 where the fluctuations seem to be higher comparatively to those observed with the PD subjects. These results for individuals are corroborated for all the population in fig. 2 where the variations are higher in average for the healthy population compared to the PD population.

In the PD cases, the smaller variations could reflect less adaptation possibilities ability in the neuromuscular response of PD patients compared to healthy people. This kind of result

was also previously observed in [9] where the modulation and amplitude of leg extensor EMG activity were reduced for the PD patients. This can be interpreted as less adaptation abilities for PD due to stereotyped activation schemes.

An increase of the STD values can be noticed at the middle of the graphs for the two PD subjects #1 and #2 (fig. 4 and fig. 5). This could be the expression of possible positive effect of medication for these two subjects (this was not encountered for all the subjects) since higher than PD STD values were obtained for healthy subjects.

## IV. Conclusion

In this paper, we have proposed a new modeling technique for the electromyographic signals based on the fractional linear prediction. This tool has been applied on real EMG data recorded in walking conditions on the *Soleus* muscle. The results have shown that dynamics of FLP coefficients for persons suffering from Parkinson's disease were lower than for healthy ones. This suggests less adjustment possibilities in the neuromuscular response of the suffering subjects compared to the healthy subjects.

The obtained results are preliminary ones but promising: it is the first time FLP modeling was used in order to assess dynamic model changes of sEMG data.

The connection with fractional Brownian motion and fractal measures of stability (via the Hurst estimators) could be an interesting perspective of this work since previous studies have investigated the fractal character of EMG data in stationary case [5] [10]. These studies have to be extended for the nonstationary case.

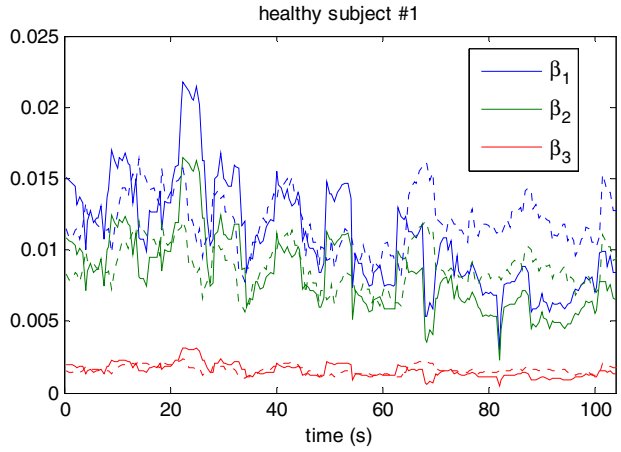


Figure 3. Time evolution of the standard deviation values of the three FLP coefficients $\{\beta_1, \beta_2, \beta_3\}$ of surface EMG for a healthy person. The full lines are for LEFT *Soleus*; dashed lines are for RIGHT *Soleus*.

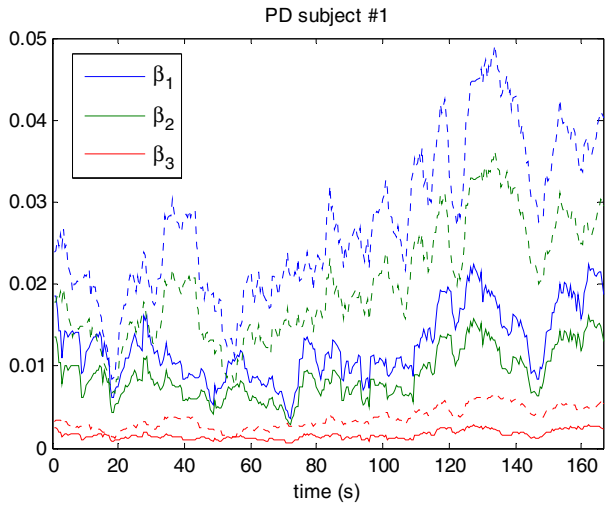


Figure 4. Time evolution of the standard deviation values of the three FLP coefficients $\{\beta_1, \beta_2, \beta_3\}$ of surface EMG for a PD #1 person. The full lines are for LEFT *Soleus*; dashed lines are for RIGHT *Soleus*.

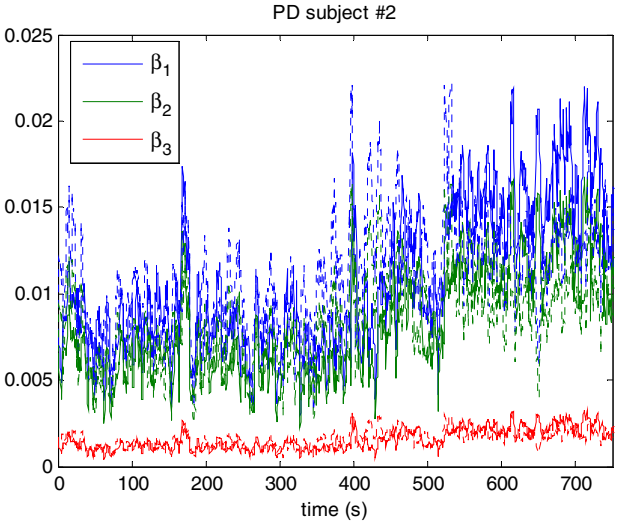


Figure 5. Time evolution of the standard deviation values of the three FLP coefficients $\{\beta_1, \beta_2, \beta_3\}$ of surface EMG for a PD #2 person. The full lines are for LEFT *Soleus*; dashed lines are for RIGHT *Soleus*.

## Acknowledgment

The present work is embedded in a French national project ECOTECH (www.echostechsan.org) and is supported by the French National Agency for research under the contract Nr ANR-12-TECS-0020.

## REFERENCES


[1] M. L. Talbi and P. Ravier, "Detection of PVC in ECG signals using fractional linear prediction," *Biomedical Signal Processing and Control,* vol. 23, pp. 42-51, 2016.

[2] R. M. D. Farina, "Comparison of algorithms for estimation of EMG variablesduring voluntary isometric contractions," *J. Electromyogr. Kinesiol.,* vol. 10, no. 5, pp. 337-349, 2000.

[3] Y. C. T. Q. Hu Sheng, Fractional processes and fractional-order signal processing - Techniques and applications, London: Springer Verlag, 2012.

[4] A. Oustaloup and M. B., La commande CRONE - scalaire au multivatriable, Hermès, 1999.

[5] K. Assaleh and W. Ahmad, "Modeling of speech signals using fractional calculus," in *Proc. 9th International Symposium on Signal Processing and Its Applications*, Sharjah, UAE, 2007.

[6] V. Joshi, R. B. Pachori and A. Vijesh, "Classification of ictal and seizure-free EEG signals using fractional linear prediction," *Biomedical Signal Processing and Control,* vol. 9, pp. 1-5, 2014.

[7] D. Valério, "Ninteger v. 2.3 Fractional control toolbox for MatLab, User and programmer manual," Universidade técnica de lisboa instituto superior técnico, 2005.

[8] S. Bercier, R. Halin, P. Ravier, J.-F. Kahn, J.-C. Jouanin, A.-M. Lecoq and O. Buttelli, "The vastus lateralis neuromuscular activity during all-out cycling exercise," *J Electromyogr Kinesiol,* vol. 19, pp. 922-930, 2009.

[9] V. Dietz, W. Zijlstra, T. Prokop and W. Berger, "Leg muscle activation during gait in parkinson's disease: adaptation and interlimb coordination," *Electroencephalography and clinical neurophysiology,* vol. 97, pp. 408-415, 1995.

[10] P. Ravier, O. Buttelli, R. Jennane and P. Couratier, "An EMG fractal indicator having different sensitivities to changes in force and muscle fatigue during voluntary static muscle contractions," *Journal of Electromyography and Kinesiology,* vol. 15, pp. 210-221, 2005.

[11] T. Kaczorek, Selected Problems of Fractional Systems Theory, Springer Verlag, 2011.