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Sampling and Digital Filtering Effects When Recognizing Postural Control with Statistical Tools and the Decision Tree Classifier

Luiz H. F. Giovanini[1,2], Simone M. Silva[1,3], Elisangela F. Manffra[1,3] and Julio C. Nievola[1,2]

[1]*Pontifícia Universidade Católica do Paraná, Curitiba, Paraná, Brazil*

[2]*Programa de Pós-Graduação em Informática*

luizgiovanini@gmail.com, nievola@ppgia.pucpr.br

[3]*Programa de Pós-Graduação em Tecnologia em Saúde*

si_massaneiro@hotmail.com, elisangelaferretti@gmail.com

Abstract

The postural control can be investigated from time series data of the center-of-pressure (COP) displacements. Detrended fluctuation analysis and scaled windowed variance are commonly employed to measure fractality in COP signal, while sample entropy and multiscale sample entropy are often used to address its regularity and complexity, respectively. Based on COP data from 19 post stroke adults and 19 healthy matched subjects, we first support previous findings that the sampling and/or the digital filtering of those data may influence the interpretations on postural control provided by such types of metrics. Then, we show evidences that the digital filtering lead to less accurate information on the entropy in postural sway with either traditional statistical tools or the decision tree (DT) classifier. Thus, when computing entropy-related features, it is not advisable to filter the data. However, if fractal features are considered instead, the use of digital filters and downsampling techniques can provide more discriminative information. When combining fractal and entropy-related features, both original and processed COP data should be considered for either DT or other popular classifiers. Lastly, with the aid of a DT, we could classify the individuals with an accuracy of 77.6% for fractal features only (best case), 68.4% for entropy-related features only, and 76.3% after combining fractal and entropy-related features.

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1 Introduction

The posturography is a well-known, widely used technique within the motor control field to measure the natural sway exhibited by the human body in the quiet stance[1]. This is usually done with the help of a force platform to obtain time series data of the center-of-pressure (COP) displacements in the anterior-posterior (AP) (i.e., sagittal plane) and medial-lateral (ML) (i.e., frontal plane) directions[1]. The parameterization of the COP signal provides metrics that can be used as clinical indicators for many useful purposes, including decisions upon rehabilitation programs. For example, the scaling exponent provided by the detrended fluctuation analysis[2] (DFA-α) has been largely adopted to measure long-range correlations (or fractality) in COP signal, providing information on the regularity (or predictably) of the body sway patterns. Sample entropy (SE) is

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another metric commonly used to address regularity in postural control. Thus, the reliability of such metrics and the interpretations that they provide may affect the diagnostic and treatment of people with impaired balance control.

In the literature, a large number of posturographic metrics have been designed not only for the COP displacement (COPd) signal but also for the COP velocity (COPv), which is indeed the most accurate form of sensory information used to maintain the upright stance[3]. They are mainly organized into magnitude metrics, related to the overall amount of postural sway, and structural metrics, associated with the temporal patterns in the sway dynamics[1]. In the motor control community, there is too much interest in finding metrics able to characterize and distinguish the underlying mechanisms of postural control of different populations. Over the last decades, it has been done with traditional statistical tools, where the candidate metrics are individually compared across groups or balance tasks[1]. More recently, however, studies in the machine learning field have successfully employed supervised classification methods for this purpose (see, e.g., ref.[4]), where it is possible to combine multiple clinical indicators to perform pattern recognition.

There is a lot of variation on how the COP data are acquired and processed in the literature[1], mainly in terms of sampling frequency and digital filtering, which may affect the structures of the signal[5]. Accordingly, ref.[5] has shown that structural metrics like DFA-α and SE are sensitive to those processing techniques, especially when they are computed from COPv rather than COPd. In fact, the statement "preprocessing tools may impact downstream conclusions" is something well-known by the signal processing community and spans over many other databases and research fields beyond postural control. Even so, this is a very important matter as it helps to build guidelines on how much the results actually reflect the observed phenomenon and how much they are being influenced by processing techniques. Thus, it is important to highlight some limitations observed in ref.[5]. First of all, the conclusions were drafted from a small sample of eight young healthy subjects performing only a single balance task, and only COP data in AP direction were analyzed. Furthermore, critical remarks on DFA-α were given in ref.[6], which has concluded that it is always important to prove the results with another method. Hence, to the best of our knowledge, further investigations are needed to provide more reliable directions on how acquisition and processing tools may affect the interpretations reached with structural metrics.

Additionally, even knowing that the sampling and the digital filtering of the COP data may influence the conclusions on postural control[5], it still remains unclear whether original or processed data are better to distinguish the postural strategies adopted by different populations, which poses a big challenge in the motor control field. Therefore, using statistical tools and a machine learning model, our main purpose in this paper is to investigate the effects of those processing tools for recognizing healthy and post stroke individuals based on structural metrics. Stroke is the leading cause of serious, long-term disabilities in the US and has figured as the second leading cause of death throughout the world in 2000 (5.7 million deaths) and 2012 (6.7 million deaths)[7].

Based on four structural metrics — two fractal and two entropy-related — extracted from COP-AP and COP-ML data of 19 post stroke adults and 19 healthy matched subjects performing two quiet standing balance tasks, this paper has the following contributions. First, we show that unfiltered data are better to address the entropy in postural control with either statistical tools or the decision tree (DT) classifier. Thus, when computing only entropy-related features from COP time series, it is not advisable to process them. However, things change when using fractal metrics instead. In this case, if statistical tools are considered, our findings encourage one to employ digital filtering and downsampling to the data, whereas both original and processed versions of the COP signals are relevant for the DT model. When combining fractal and entropy-related features, it is also advisable to consider both original and processed COP data for either DT or other popular classifiers. With a DT learned from entropy-related features, we established a cut-off score that allows one to distinguish between healthy and stroke individuals with 68.4% of accuracy. We also provided a DT based on fractal metrics able to recognize such groups with 77.6% of accuracy. Lastly, we show that the DT is competitive to other popular machine learning methods to distinguish healthy from stroke sway profiles.

The rest of the paper is organized as follows. First, we motivated our experiments in section 2. Then, we present and discuss our results in section 3. Finally, we conclude and discuss future work in section 4.