Information theoretic analysis of EMG and kinematic data among runners with patellofemoral pain

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Abstract: More than a third of the US population engaged in running in 2018, and the rate of lesions in inexperienced runners is higher than 80%. Often, the diagnosis of lesions in the lower limb require extensive evaluations, including gait analysis. Such analysis look for differences in pathological and normal gait, and are often conduced by health professionals which monitor myoelectric impulses and the kinematic. Yet both EMG and Kinematic are related, many challenges surround the full comprehension of this coupling. Information theoretic measures are known for discovering the dependency between variables, and have already been used for the analysis of muscle synergy and on EEG signals. This work contains a case study of the usage of Delayed and Conditional Mutual Information on healthy individuals and patellofemoral pain patients, and presents some differences found in the muscle activation patterns between both groups.

Keywords: Electromyography, Kinematic analysis, Information theory, Mutual information, Patellofemoral pain.

1. INTRODUCTION

Though the prevalence of gait disorders increases steeply with age – from 10% around the age of 60, to 60% on those over 80 years old (Mahlknecht et al., 2013) – ageing is not the only nor the most worrying cause of gait disorders: 60% of patients with neuromuscular disorders – such as stroke (Kim et al., 2016), spinal cord injuries (Tan et al., 2021), normal pressure hydrocephalus (Davis et al., 2021), Parkinson's disease (Bello et al., 2019), etc. – have a form of walking disability (Rodriguez-Fernandez et al., 2021), and repeated minor lesions during sport practices or daily activities can also cause more serious gait disorders (Moisan et al., 2019).

Lesions caused by running are a particular cause of concern, since in the United States 110 million people (1/3 of the population) engaged on this type of activity in 2018 (Statista, 2020), and the rate of injury in this sport varies from 3.2% for cross-country runners to 84.9% in inexperienced runners (Kluitenberg et al., 2015). Lesions usually lead to the lack of physical activity, increasing the risk of developing a secondary health condition, and decreasing the life expectancy of the patient. Therefore, rehabilitation is one of the main goals of physicians treating gait disorders (Rodriguez-Fernandez et al., 2021).

Instrumented gait analysis can provide comprehensive data on normal and pathological gait, which are useful in the clinical practice for obtaining information about joint motion, movements, timing and action of the muscle, contributing for understanding the walking patterns and identifying the causes of a gait irregularity (Guo et al., 2020; Agostini et al., 2020). The kinematic analysis of the gait leads to a better perspective on how individuals use their combination of strength, flexibility and muscle memory to achieve gait, allowing more direct approaches to diagnosing and treating any abnormalities (Dicharry, 2010). On the other hand, the knowledge about the muscles activities during abnormal gait can help physicians to support their diagnosis, design better surgical interventions, design and evaluated rehabilitation in personalized manner, evaluate muscle fatigue and support forensic medicine with objective outcomes (Agostini et al., 2020). Despite the various clinical applications, instrumented gait analysis is still underutilized (Agostini et al., 2020; Dicharry, 2010).

Many challenges still surround the comprehension of the gait, mainly the EMG to kinematic coupling (Cruz-Montecinos et al., 2020; Jorge et al., 2018; Kelencz et al., 2017). Combined to difficulties in interpretability due to large intra-subject variability (Stokes et al., 2017; Patikas, 2016), though there is a relevant number of studies (Cruz-

Montecinos et al., 2020; Jorge et al., 2018; Kelencz et al., 2017; Stokes et al., 2017; Patikas, 2016) supporting the usage of these signals in gait analysis, those factors limit the widespread use into routine clinical practice (Hong et al., 2020; Guo et al., 2020; Agostini et al., 2020; Dicharry, 2010).

Mutual Information (MI) is one of several methods for analyzing the dependency between time series (Runge, 2014). It is an information theoretic and non-parametric measure of linear and non-linear dependency between two variables (Kvålseth, 2017), which complies to the notion that real-world time series are usually non-stationary and non-linear (Wan and Xu, 2018).

Through the analysis of MI between signals over the time, on what is called Delayed Mutual Information (DMI), it is possible quantify the information shared across time series, taking into account previous information as function of time (Tsukahara. et al., 2020). Endo et al. (2015) have shown that DMI is an option for analyzing nonlinear system such as myoeletric data, and Afsar et al. (2018) used DMI to develop the gait forces profile on Parkinson patients. To evaluate neural interactions between muscles during postural tasks, Boonstra et al. (2019) used the Conditional Mutual Information (CMI), which quantify the expected value of the mutual information of two random variables given a third one.

This paper seeks to perform a case study using Delayed and Conditional Mutual Information, to verify the interaction among EMG and Kinematic signals. In addition, these measures will be compared between healthy individuals and patients of patellofemoral pain. In section 2 it is described the theory of DMI and CMI. Section 3 presents the data used and the applied methodology. Section 4 presents and the achieved results and Section 5 the discussion. Finally, section 6 contains the conclusions.

2. MUTUAL INFORMATION

The measure of how much uncertainty is in a given random variable can be determined through its entropy (H), defined by Shannon (1948) as

$$H(X) = -\sum_{x\in X} p(x)\ \log_2 p(x) \tag{1}$$

where X is a discrete random variable and $p(x) = P\{X = x\}$ is the probability mass function of X. The entropy is measured in bits, since the logarithms base is 2.

Given two signals X and Y, the Mutual Information between them, $MI(X;Y)$, quantify how much it is possible to reduce the uncertainty of X given the knowledge of Y (Cover and Thomas, 1991). This can be calculated by

$$MI(X;Y) = \sum_{x\in X}\sum_{y\in Y} P(x,y)\ \log_2 \frac{p(x,y)}{p(x)p(y)} \tag{2}$$

The Delayed Mutual Information (DMI) uses the same mathematical framework of the MI, but with Y delayed by some time t. This allows quantifying how much the uncertainty of X can be reduced by the knowledge of a previous state of Y. This can be calculated as a function of a delay τ, by

$$DMI((X;Y),\ \tau) = MI(X(t);\ Y(t-\tau)) \tag{3}$$

The conditional dependency between two variables X and Y, given a third random variable Z $CMI(X;Y|Z)$, can be measured by the Conditional Mutual Information. It is defined as

$$CMI(X;Y|Z) = \sum_{x\in X}\sum_{y\in Y}\sum_{z\in Z} P(x,y,z)\ \log_2 \frac{p(z)p(x,y,z)}{p(x,z)p(y,z)} \tag{4}$$

The CMI can also be calculated as a function of a delay τ in order to evaluate the changes in the conditional relations over time, by

$$DCMI((X;Y|Z),\ \tau) = CMI(X(t);\ Y(t-\tau)\mid Z(t)) \tag{5}$$

However, since all of above MI measures the shared information between two variables, its value is relative to the total information content of these variables, and consequently MI cannot be compared between datasets. A solution for this problem is the usage of normalized MI (NMI), which is bounded and can be compared across datasets (Bingham et al., 2017):

$$NMI(X;Y) = \frac{MI(X;Y)}{min(H(X),H(Y))} \tag{6}$$

Normalization can also be made on CMI (Kvålseth, 2017), by

$$NMI(X;Y|Z) = \frac{MI(X;Y|Z)}{min(H(X|Z),H(Y|Z))} \tag{7}$$

According to Cover and Thomas (1991) the channel capacity C is given by the maximum measure of Mutual Information

$$C = \max\ MI(X;Y) \tag{8}$$

and Proakis and Salehi (1994) demonstrated that the channel capacity for DMI is quantified by its peak value.

The transmission rate estimation R, also described by Proakis and Salehi (1994), can be written as a function of channel capacity and signal bandwidth (BW) in Hertz:

$$R = 2\cdot BW\cdot C \tag{9}$$

If the entropy is measured in bits, the transmission rate is going to be measured as bits/s.

3. METHODS

Data was obtained from two different datasets, collected by the Laboratory of Orthopedics and Traumathology

ISSN: 2525-8311

DOI: 10.20906/CBA2022/3584

Evaluation and Intervention (LAIOT), of the São Carlos Federal University (UFSCar) in São Carlos, Brazil.

Dataset 1 contains kinematic and electromyography data from 5 healthy participants. *Dataset 2* contains kinematic and electromyography data from 5 individuals with patellofemoral pain (dos Santos et al., 2016).

Both datasets were collected during a 30-second run, using the same methodology. The three dimensional joint kinematic of the trunk, hip, knee and foot was collected at 240 Hz, filtered at 6 Hz using a fourth-order zero-lag low-pass Butterworth filter (Willson and Davis, 2008), and the Euler angles calculated using a joint coordinate system recommended by the International Society of Biomechanics (Vaughan et al., 1992). The electromyography signals were sampled at 2400 Hz, recorded unilaterally in a frequency band from 20 Hz to 500 Hz.

Each patient had 5 biosignals collected: 1 kinematic – the angle of the knee in the sagittal plane – and 4 myoelectric – the activations of the *Biceps femoris*, *Gastrocnemius*, *Rectus femoris* and *Tibialis anterior* muscles.

Upon collection, the EMG signals were filtered with a zero-lag Butterworth Filter. Then, the envelope was obtained using the Hilbert Transformation. Although the envelope has already smoothed the signal, it still has high frequency components which will be removed with a zero-delay Savitzky-Golay (S-G) filter. The S-G filter is a digital moving-average filter, capable of smoothing the signal without distorting the original tendency (Acharya et al., 2016). Lastly, all EMG signals were resampled in order to decrease the sample-rate to 240 Hz using a polyphase FIR filter with coefficients calculated using a Kaiser window.

Both EMG and Kinematic signals have *quasi-periodic* behavior, with similar periods. Both signals were normalized by their median and variance in order to be compared using the same scale. To analyze this dependencies Mutual Information (MI) was used.

The interaction between muscular activations and the kinematic responses can be seen as causal, since myoelectric impulses are biologically responsible by the movement, and therefore a delayed interaction between the EMG and Kinematic signals is expected. While the DMIs are a good indicator of the interaction of EMG and Kinematic signals between themselves and with each other, they are a pairwise measurement. Therefore, normalized Delayed Conditional Mutual Information (DCMI) were taken between two EMG signals given a Kinematic one.

4. RESULTS

Stationarity was observed on the signals allowing the usage of Shannon's entropy measure. Table 1 presents the measure of Entropy, in bits, for each signal of each individual analyzed. Individuals whose code start by H are healthy and the ones starting by P are diagnosed with patellofemoral pain.

The nomenclature used for the signals was BF for *Biceps femoris* electromyography, RF for *Rectus femoris*, TA for *Tibialis anterior*, GC for *Gastrocnemius* and KN for the angle of the knee in the sagital plane.

The DMI was calculated for EMG and Kinematic signal pairs, and the results of the channel capacity, obtained from the DMI peak, are displayed in Table 2. Table 3 presents the bandwidth, in Hz, for each signal.

Table 4 contains the Transmission Rate, in bits/s, for each of the EMG-Kinematic pairs. A box-plot of the transmission rate's mean and standard deviation is shown in Figure 1.

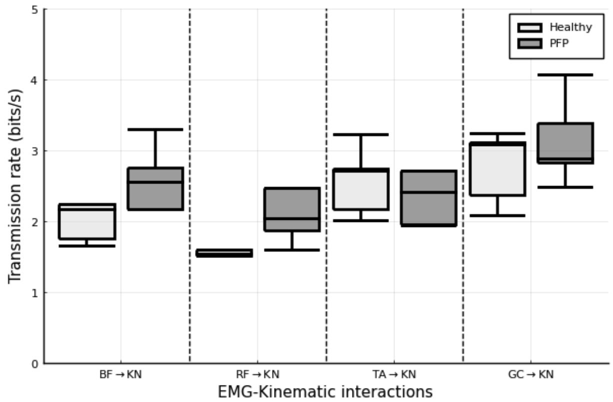

Figure 1. Box-plot of the transmission rate's mean and standard deviation, in bits/s. Dark grey represents healthy individuals, while light grey represents PFP patients.

To verify if PFP patients and healthy individuals use the muscle in the same way, a Delayed CMI was calculated for GC and TA given KN and the results are present in Figure 2. This heat map shows the expected value of the mutual information between *Tibialis anterior* and *Gastrocnemius* myoelectric impulses when the angle of the knee in the sagittal plane is known.

The CMI in healthy individuals shows have higher peaks. An analysis of the Standard Deviation in the CMIs was conducted, and Figure 3 shows the box-plot of the normalized SD in four different Delayed CMIs between two muscles given the angle of the knee.

5. DISCUSSIONS

The data from all of the individuals analyzed was collected in the same manner while they were performing the same task – walking in a treadmill. Since all of those individuals are capable of walking, it can be inferred that myoelectric impulses on both healthy and PFP individuals are the

Table 1. Entropy calculated for all individuals and signals used in the case study, given in bits.

Individual	BF	RF	TA	GC	KN
H1	4.892	4.04	4.962	4.553	6.017
H2	5.025	4.092	5.67	4.819	6.045
H3	4.383	3.291	5.008	3.998	6.157
H4	4.339	4.397	5.362	3.758	6.187
H5	4.794	3.123	5.691	3.897	6.092
P1	5.18	5.364	5.208	4.257	6.187
P2	5.393	4.947	4.335	3.627	6.091
P3	5.133	5.415	5.517	4.378	6.083
P4	5.496	4.054	5.18	4.12	6.029
P5	5.1	4.099	5.197	4.151	6.053

ISSN: 2525-8311

DOI: 10.20906/CBA2022/3584

Table 2. Channel capacity in bits for all individuals.

Individual	BF → KN	RF → KN	TA → KN	GC → KN
H1	0.92	0.795	1.137	1.247
H2	1.029	0.755	1.533	1.465
H3	0.956	0.927	1.173	1.332
H4	1.073	0.828	1.311	1.354
H5	1.413	0.664	1.174	1.4
P1	1.084	1.047	0.83	1.226
P2	1.028	0.762	1.011	1.261
P3	0.952	1.035	1.141	1.175
P4	1.141	0.984	1.019	1.308
P5	1.03	0.755	1.146	1.342

Table 3. Bandwidth calculated for all individuals and signals used in the case study, given in Hz.

Individual	BF	RF	TA	GC	KN
H1	4.991	5.031	6.431	4.863	4.248
H2	4.594	4.562	4.409	4.429	2.847
H3	5.007	4.537	4.977	4.456	2.026
H4	11.912	4.872	7.697	4.149	2.251
H5	4.928	5.29	5.83	3.958	2.991
P1	4.606	5.27	6.107	4.714	8.426
P2	8.536	5.591	8.84	3.932	1.222
P3	5.826	5.156	6.532	4.359	9.218
P4	5.377	4.968	5.274	5.197	2.662
P5	4.058	4.578	4.088	11.466	3.19

Table 4. Transmission rate in bits/s for all individuals.

Individual	BF → KN	RF → KN	TA → KN	GC → KN
H1	1.753	1.514	2.166	2.375
H2	2.166	1.59	3.227	3.085
H3	2.238	2.169	2.744	3.118
H4	1.648	1.271	2.013	2.079
H5	3.271	1.537	2.718	3.241
P1	2.551	2.463	1.952	2.884
P2	2.755	2.041	2.709	3.377
P3	3.302	3.591	3.959	4.075
P4	2.167	1.87	1.935	2.484
P5	2.173	1.594	2.418	2.831

cause for the kinematic responses. This hypothesis is supported by the similar results of entropy and transmission rate found across all of the experiments.

Some of the healthy subjects showed a similar CMI map over (TA, GC | KN), with a high CMI near the antidiagonal and a repeating pattern of two higher CMI areas near from one another. Having a high CMI near the antidiagonal indicate that the information on the knee angle within the same time, but when one or both signals are delayed with different times, the CMI decreases, indicating they have less information on the position of the knee in the sagittal plane. This probably indicates a joint activation pattern between such muscles, which is supported by Vaughan et al. (1992).

The CMI from PFP patients are similar between each other, but with different characteristics from the ones calculated from healthy patients signals. Now, patterns in the antidiagonal are less visible, giving place to a CMI pattern in the form of vertical or horizontal lines. A vertical or horizontal peak of CMI indicates that one of the muscles have more information about the knee than the other, suggesting their activations are now unsynchronized.

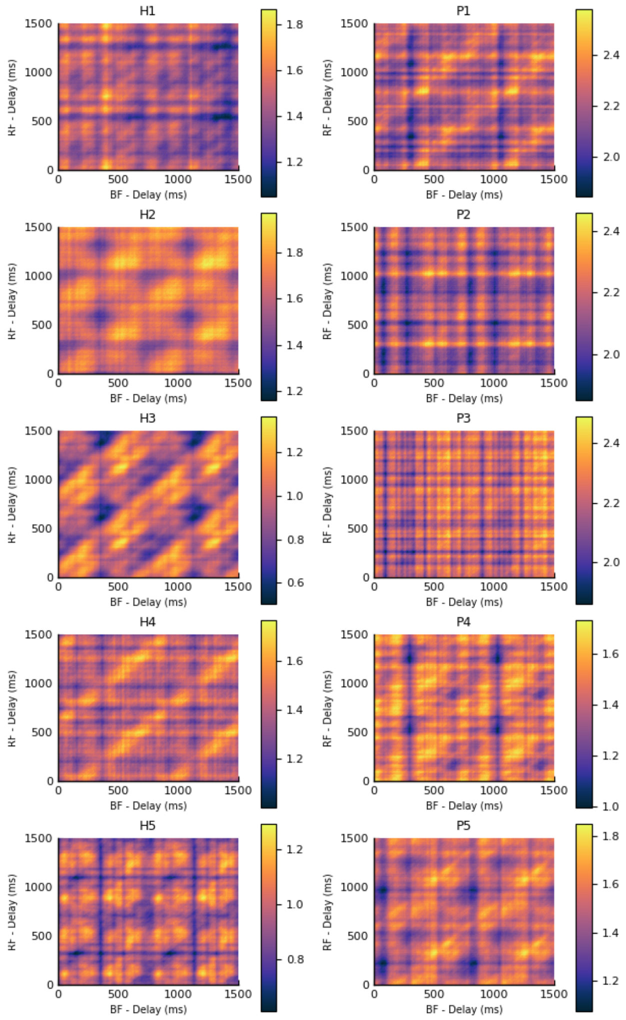

Figure 2. Normalized Conditional Mutual Information between the myoelectric activation of *Tibialis anterior* (TA) and *Gastrocnemius* (GC) given the Knee Angle in the Sagittal plane. Plots on the left are from healthy individuals, and on the right from PFP patients.

Mutual Information analysis were a good indicative that there are some underlying relationships between kinematic and electromyography data that might be unsensitive to inter-subject variability, and that may also allow the classification of healthy and unhealthy patients. To verify this hypothesis, the CMI maps for 4 different cases were merged and the standard deviation (SD) was than analyzed.

The SD of the CMI in PFP patients had a lower mean in all of the 4 cases analyzed, and a lower interval in three of them. The separation between Healthy and PFP patients was more noticeable in the first and third cases, where the interval of the CMI standard deviation in PFP patients was below to the mean of the analysis using healthy patients data.

Both of the more separable cases included the *Biceps femoris* in the analysis, suggesting that it is activated differently in healthy and PFP patients. This is also supported by the Transmission Rate analysis, where the *Biceps femoris* displays a slightly smaller rate in Healthy patients than in PFP patients.

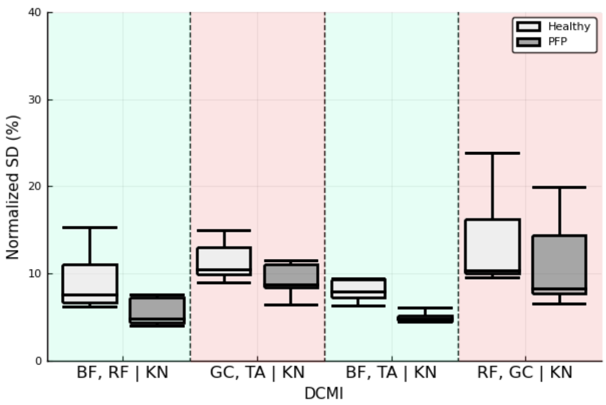

Figure 3. Box-plot of the normalized Standard Deviation of the DCMI in 4 different triplets. Dark grey represents healthy individuals, while light grey represents PFP patients. The background color indicates the separation between Healthy and PFP patients: green background shows a good separation and red shows an overlap.

6. CONCLUSIONS

This research presents an approach for verifying the interaction between EMG and Kinematic signals using Delayed and Conditional Mutual Information. This measures were also compared across healthy and patellofemoral pain patients.

Detecting a pattern in the Delayed Mutual Information function across patients, specially between Kinematic and EMG signals is a clue that these signals are related to each other. The relations found in the CMI also reflect the biomechanical understanding that the *Biceps femoris*, *Rectus femoris*, *Tibialis anterior* and *Gastrocnemius* muscles are all related to the movement of the knee, but with different activation patterns, reinforcing that the development EMG-kinematic coupling model is possible despite of inter-subject variability.

Differences between the Conditional Mutual Information are also an indicator that there are changes in the Kinematic-EMG coupling among healthy subjects and individuals with Patellofemoral Pain. The *Biceps femoris* muscle had the most noticeable difference, therefore indicating that the analysis of such muscle during gait may be a path to better understanding the gait in PFP patients.

ACKNOWLEDGEMENTS

This work was partially supported by the CNPq grants no. 465755/2014-3; 130859/2020-6; FAPESP grants no. 2014/50851-0 and 2018/19150-6.

ETHICS STATEMENT

The testing protocol was approved by the Federal University of São Carlos Ethics Committee for Human Investigations (protocol number 735.596), and the subjects signed a written informed consent form to participate in this study.

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