BIOMECHANICAL COMPLEXITY: A MEASURE TO DELINEATE BETWEEN ATHLETIC GROIN PAIN PATIENTS AND UNINJURED CONTROLS

Shane Gore[1,4,5], Andrew Franklyn-Miller [1,2], Chris Richter[1], Eanna Falvey[1,6], Enda King[1,3] and Kieran Moran [4,5]

Sports Medicine Department, Sports Surgery Clinic, Santry Demesne, Dublin, Ireland[1]
Centre for Health, Exercise and Sports Medicine, University of Melbourne, Australia[2]
Department of Life Sciences, Roehampton University, UK[3]
School of Health and Human Performance, Dublin City University, Dublin, Ireland[4]
INSIGHT Centre for Data Analytics, Dublin City University, Dublin, Ireland[5]
Department of Medicine, University College Cork, Ireland[6]

This study investigates if signal complexity is a useful measure to delineate between patients diagnosed with athletic groin pain (AGP) and uninjured controls. The 3D biomechanics of 65 AGP patients and 50 uninjured controls were examined during a lateral hurdle hop exercise. The complexity of hip moments was examined using quadratic sample entropy and statistically tested using independent t-tests. The results from this study demonstrated that the AGP group had significantly less complexity in hip moments in comparison to the uninjured control group with effect size ranging from 0.53 - 0.96. These findings would suggest that signal complexity of hip moments may be a useful measure to distinguish between those with and without AGP.

KEY WORDS: Non linear variability, screening, Injury

INTRODUCTION: Biomechanical analysis of field sport injuries [including athletic groin pain (AGP)] has traditionally focused on magnitude-based representation (e.g. maxima and minima values) of biomechanical signals using discrete or continuous signal analysis. However, the structure of a signal, for example its complexity, is also a rich source of additional information (S. Pincus & Huang, 1992). Complexity refers to the deterministic structural richness contained within a signal that emerges from the dynamic interaction of multiple components, organized around and summating to an outcome goal (Komar, Seifert, & Thouvarecq, 2015). Pathology or injury is theorized to reduce the degrees of freedom available to the system to achieve a movement task and hence there may be a reduction in signal complexity (Harbourne & Stergiou, 2009). Whilst recent research has begun to examine the biomechanics of AGP using traditional metrics, including examinations of stiffness and measures of variability, to date no research has examined complexity in AGP patients and its ability to delineate between injured and uninjured controls.
It has been suggested that the hip joint is particularly important in the pathomechanics associated with AGP (Franklyn-Miller et al., 2016). During dynamic weight bearing tasks the hip joint works to transfer load from the lower limb to pelvis and any alterations in hip mechanics will alter the resultant hip joint force (Lewis, Sahrmann, & Moran, 2010). This in turn may overload the commonly painful pubic symphysis region and the adjacent muscular, ligamentous, and cartilaginous structures, which act to stabilise it (Meyers, Greenleaf, & Saad, 2005). The purpose of this investigation was therefore to examine complexity in hip joint moments in AGP patients in comparison to uninjured controls. It was hypothesised that the AGP group would have significantly lower complexity when compared to an uninjured group.

METHODS: Sixty-five male subjects with AGP (mean ± *SD:* age 24.6 ± 4.8 yrs., height 180.5 ± 5.8 cm, mass 81.5 ± 8.5 kg), along with fifty male controls (mean ± *SD:* age 23.9 ± 3.4 yrs.,

height 179.7 ± 9.26 cm, mass 79.8 ± 13.8 kg) participated in this study. Each participant attended the lab on one occasion for a biomechanical examination of the lateral hurdle hop test. This test involved a lateral hop over a 15 cm hurdle followed by an immediate hop back to the initial starting position. The AGP participants were examined on their symptomatic side, contra lateral leg flexed at a 90-degree angle and hands unrestricted for balance. The uninjured control group were matched proportionally for leg dominance. Participants were instructed to undertake the hop as explosively as possible. Three repetitions of this exercise were undertaken to obtain mean scores. Eight infrared cameras (250Hz; Vicon, UK), synchronized with two force platforms (1000Hz; AMTI, USA), were used to collect data. Reflective markers were placed at bony landmarks according to Plug-in-Gait marker locations (Vicon, UK). Marker and force data were filtered using a fourth order low pass Butterworth filter at 15 Hz. The data was subsequently exported to Matlab 2013b (Mathworks, USA), where signal entropy was calculated and the statistical analysis conducted. To calculate signal entropy, hip moments were examined during the period of initial contact to toe off. Initial contact and toe off were defined respectively as the instances at which the vertical ground reaction force exceeded and fell below a 5N threshold. No time normalisation procedures were performed to avoid any kind of alteration to the dynamics of time series. Entropy was calculated using quadratic sample entropy as outlined in Lake & Moorman (2011). The underlying concept of entropy is that in simple waveforms, sequences or subsections are repeated regularly, while this is not the case in a complex wavefrom. In this respect, the first step of calculating quadratic sample entropy is to calculate the conditional propability that two short subsections of a waveform that match within a tolerance of acceptability will continue to match at the next point. This calulation is termed sample entropy and is calculated as follows: given a waveform containing t consecutive data points ($x_1, x_2, x_3 \ldots x_t$), a subsection of this waveform of length m<t and starting at point i ($x_i, x_{i+1,\ldots} x_{i+m-1}$) is termed a template [$Temp_m(i)$]. This template is compared to subsequent subsections of length m within the total waveform. Every time a match between the template and subsequent subsections of the waveform is observed within an acceptable tolerance of disimilarity (r >0), the match is counted and their conditional probabilities are summed and divided by t – m. This creates the variable A. This process is then repeated for [$Temp_{m+1}(i)$] creating the variable B. The sample entropy (equation 1) is then calculated as the negative natural logarithm of the conditional probability of a match of length m+1 given a match of length m:

$$Sample\ Entropy = -ln\ (A/B) \qquad (1)$$

Quadratic sample entropy can then be calculated by adding the natural logarithm of 2r, thereby removing the influence of the size of t through normalisation (Lake & Moorman, 2011) (equation 2):

$$Quadratic\ sample\ entropy = Sample\ Entropy + ln\ (2r) \qquad (2)$$

For this study, quadratic sample entropy was calculated with m = 2 and r = 0.2*standard deviation of the signal being examined (S. Pincus & Huang, 1992). A series of t-tests were utilised to compare AGP results to uninjured results, however no adjustment for multi comparisons was deemed necessary (Hopkins, Marshall, Batterham, & Hanin, 2009). All results are presented as mean ± SD and Cohen's effect size was reported as small (0.2 – 0.5), medium (0.5 – 0.8), and large (> 0.8).

RESULTS: Complexity was significantly less in the AGP group in comparison to the control group at the hip in all three planes with effect sizes ranging from medium to large (Table 1).

Table 1: Mean Quadratic sample entropy for hip moment waveforms (ordered in terms of effect size – D).

Variable	AGP Pre	Uninj Controls	AGP Pre vs. Uninj Controls	
	Mean ± SD	Mean ± SD	D	Sig
Hip Flex/Extensor	-0.50±0.45	-0.05±0.37	0.96	< 0.01
Hip Ab/Adductor	-0.97±0.30	-0.75±0.34	0.67	< 0.01
Hip Int/Ext Rotator	-2.20±0.32	-2.03±0.32	0.53	0.01

AGP = athletic groin pain, Uninj = Uninjured, D = Cohen's D effect size, Sig = significance (p).

DISCUSSION: This study sought to investigate if biomechanical complexity was a useful measure to delineate between those with and without AGP during a lateral hurdle hop task. Overall the AGP had significantly less complexity in hip moments as measured by quadratic sample entropy in comparison to the uninjured control group. The lower joint moment complexity observed in the AGP group is supported by previous gait research indicating that injured individuals with chronic ankle instability (Terada et al., 2015) and knee osteoarthritis (Tochigi, Segal, Vaseenon, & Brown, 2012) have lower complexity in measures of ankle frontal plane kinematics and tri-axial leg accelerations, respectively. In other domains, lower signal complexity has also been identified in centre of pressure data in concussed athletes (Cavanaugh et al., 2006) and in various pathological biological signals including: heart rate atrial fibrillation (Lake & Moorman, 2011) and electroencephalograms in Alzheimer's disease (Simons, Abasolo, & Escudero, 2015).

While the present study did not examine the underlying pathophysiology associated with this loss of complexity in AGP patients, it has been suggested within the general biological literature that reduced complexity is associated with a reduction in the number of, or the coupling and co-ordination between, sensory inputs (Cavanaugh, Guskiewicz, & Stergiou, 2005; S. M. Pincus, 1994). There are a number of potential explanations for the findings of this study. Firstly, the reduced complexity may represent a risk factor for the development of AGP as the reduced complexity could represent an inability to respond to perturbations, which are common during field-based sports. It is unclear from the present study however if complexity precedes AGP or is a result of this injury, and further research is warranted.

Secondly, it is possible that the AGP group are utilising a more regular, rigid, motor behaviour in an attempt to avoid pain (or perceived threat of pain) associated with this condition. In fact previous research has demonstrated that compensatory movements can be retained even when pain is no longer present (Tucker, Larsson, Oknelid, & Hodges, 2012). A final explanation of our findings is that the lower complexity may reflect neuromuscular detraining. Indeed previous research has demonstrated that heart rate complexity is reduced after just four weeks of detraining (Heffernan, Fahs, Shinsako, Jae, & Fernhall, 2007) and a reduction of training load is common in AGP in order to manage the pain associated with this condition (Hölmich & Thorborg, 2014).

CONCLUSION: The results from this study suggest that biomechanical complexity of hip moments is a useful measure to delineate between those with and without athletic groin pain during a lateral hurdle hop test. Future research should examine the kinetic and kinematic complexity of all lower limb joints in AGP patients and compare the findings directly to more traditional biomechanical metrics (e.g. maxima and minima measures).

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