A NOVEL METHOD TO DETERMINE STATISTICAL EFFECT MAGNITUDE USING SPM FOR GAIT ANALYSIS

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The purpose of this research was to extend the typical SPM analysis of time varying human movement gait. We focused on the magnitude of statistical effect, with colour maps used to identify regions of high and low effect at the three-component vector level (3D joint kinematics and kinetics). Conceptually similar to a multivariate ANOVA, users can easily identify joints with the highest statistical effect, then probe the scalar components to determine which is most contributing to this effect. Though the analysis can be applied to any human movement biomechanics (i.e., running, walking, landing etc.), the example presented here is walking gait. Though only the kinetics from a single joint are presented, our goal is to build a user-friendly GUI capable of analysing the kinematics and kinetics of all joints and degrees of freedom in the kinematic and kinetic chain.

KEYWORDS: SPM1D, clinical gait, analysis, time-varying.

INTRODUCTION: Following to the invention (Pataky, 2012; Pataky et al., 2013), then validation (Pataky, 2016) of the open-source analysis platform SPM1D, it is emerging as an international standard for the exploratory analysis of time varying human movement (i.e., kinematics, kinetics, EMG, GPS, etc.). The foundation of SPM1D is built upon random field theory in order to make statistical inferences regarding registered (normalized) sets of time varying measurements. Though computationally rigorous, arguably the largest benefit to this analysis platform is the elegant simplicity from which researchers and clinicians can perform statistical analyses of continuum data (Figure 1). Therein, researchers simply need to input an alpha level (e.g., 0.05) and are provided with a) where within, and b) the direction of statistically significant differences between two sets of registered time series data (i.e., two independent groups, per- post-data, reference to a normative datasets etc.).

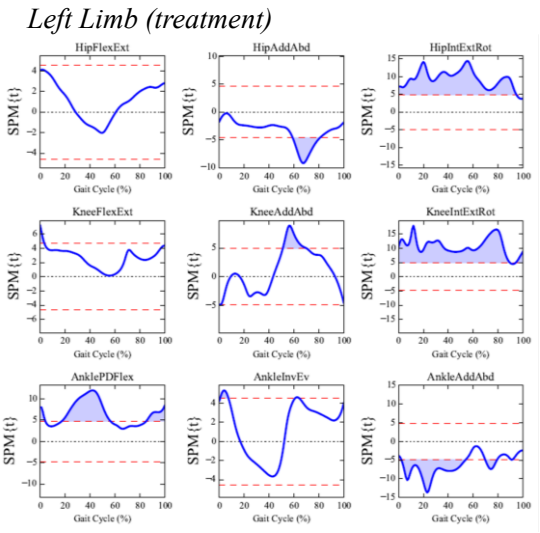

Figure 1: Depiction of current SPM1D clinical gait analysis pre- post-intervention. Image adapted from Donnelly et al. (2012).

The benefits of this analysis tool are three-fold:

1) Researchers and clinicians do not need to spend valuable research or clinical time deliberating over which 0D (discrete) variables to analyse when performing exploratory time varying analysis.
2) Researchers and clinicians are protected from regional focus bias (Pataky et al., 2013).
3) Researchers and clinicians are protected from inter-component covariation bias (Pataky et al., 2013).

Together what these benefits provide is the mitigation of risk that a researcher or clinician will make a type 1 or type 2 error in their analysis of time varying data (i.e., identifying something that is not there, or missing something that is

there). This is of particular importance for clinical populations (i.e., rehabilitation, optimal performance, etc.) as rehabilitation pathways and return to play recommendations are built on these data. In addition, small therapeutic sample sizes in rehabilitation populations also has the potential to increase the risk of such statistical errors.

From a gait analysis perspective, it could be argued that the analysis of the threshold crossings (clusters) within a given time series can be difficult to interpret. For example, looking to Figure 1 above, a clinician may not only be interested in where significant differences have occurred, but the magnitude of statistical effect of this cluster. Why this is important is so a clinicians, researchers and coaches can focus their treatment plans on the joint and joint degrees of freedom with the largest differences relative to normative populations. Alternately, they can identify which joint degrees of freedom are responding to a treatment plan or intervention the most. Lastly, it can also be argued that joints should be analysed as 3D vectors, before they are analysed with respect to their scalar components (i.e. joint or anatomical coordinate system).

The bigger purpose of this research is to build a SPM1D clinical gait analysis template. The analysis template will be focused on effect magnitude estimates, with colour maps used to identify regions of high and low effect at the three-component vector level (3D joint kinematics and kinetics), as well as the one-component scalar level. The example presented here was walking gait analysis, but the final clinician-friendly GUI is being built to handle any form of human movement condition (i.e., running, walking, landing etc.) or data (kinematics, kinetics, EMG, GPS, etc.).

METHODS: Data related to A single male patient (height: 166 cm, weight: 68 kg, age: 63) who presented with medial compartment left knee pain was collected at the Biomechanics Laboratory in Rehabilitation Research Institute of Singapore. The patient's lower limb biomechanics were assessed using three different conditions: 1) walking gait, 2) step up and down 3) sit to stand task (Figure 1). Only the results of walking gait trials (n = 7) were reported in this study.

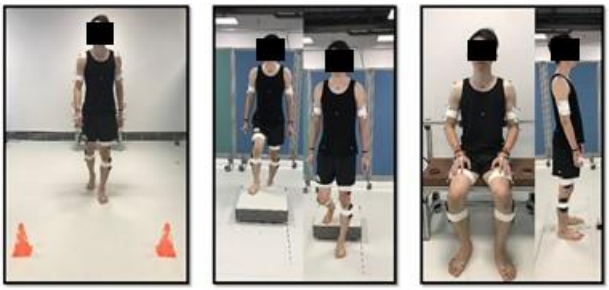

Figure 2: overview of lower limb conditions. From left to right: walking gait, step up and down, sit to stand.

A Qualisys motion capture system recording at 200 Hz, synchronised with two Kistler force platforms recording at 2,000 Hz were used to record three-dimensional kinematics and 6 DoF ground reaction forces (GRF)(i.e., motion capture data). A patient-specific lower limb laboratory-specific kinematic marker set and kinematic model similar to the Calibrated Anatomical System Technique (CAST) developed by Cappozzo et al. (1993) was used. Providing a brief overview of these procedures, ankle joint and knee joint centres were defined using anatomical landmarks on the medial and lateral malleoli and epicondyles respectively. A regression model from the pelvis markers was used to define the hip joint centres. All anatomical information was then stored within technical coordinate systems held away from joint axes of rotation. Kinematic marker trajectories and GRF data were both low pass filtered at 10 Hz using a zero-lag fourth order Butterworth filter. Direct kinematics and kinetics were calculated as per the standards of the International Society of Biomechanics (ISB) (Wu and Cavanagh, 1995).

The time varying 3D kinematics, joint moments and power of both limbs were calculated, although only joint moments are presented here. The signals were time normalised to 100% stance. Joint moments and power were amplitude normalised to body mass (kg). The SPM1D package (spm1d.org), with magnitudes of statistical effect were used to analyse all continuum

data relative a normative dataset. The normative dataset contained seven gender, age, ethnicity and body mass matched participants.

The mean 3DoF joint moment data of the seven participants used for the normative dataset were aggregated to form 3-dimensional arrays for all joints of the lower limb (size, 7 x 100 x 3). Similarly, for the patient data, seven individual walking trials for all joints of the lower limb were used to form corresponding 3-dimensional arrays. The two-sample Hotelling's T^2 test (Pataky et.al. 2013) from the SPM1D package was used to compare the 3-dimensional arrays between the normative population and the patient. The test-statistic SPM $\{T^2\}$ which is the time varying test statistic $\{T^2\}$, was yielded from the Hotelling's T^2 test. The time varying effect magnitude was defined as SPM $\{T^2\}$ divided by the critical random field theory threshold of T^2 (i.e., T^2/ T^2 threshold). This was plotted using a colour map for simple to understand visualisation of the magnitude of statistical effect for the time varying joint moments between the normative population and the patient.

The 3DoF joint moment that demonstrated the greatest level discrepancy was identified from the colour map visually, and *post hoc* analysis was performed on the scalar components of the 3DoF joint moment using a SPM two-sample {t} statistic. This was performed to identify which scalar component(s) of the 3DoF vector contributed to time varying discrepancies from the Hotelling's T^2 test. As per above, the magnitude of statistical effects were defined using t/ t-threshold over the time series.

RESULTS: Though full 3D lower limb kinematics, joint moments and joint power were analysed, due to space restrictions, we will only present the joint moments of the right (unaffected) limb, as they were the most unintuitive and interesting findindings.

As observed in Figure 3 (Page 4), the largest magnitudes of statistical effects for the right limb were observed at the ankle joint, between 70-80% of stance, which corresponded to push-off or toe-off. When looking to the scalar components of the vector, it was observed that magnitude of effect was most pronounced in the plantar/dorsiflexion degree of freedom. Moderate magnitude of effects were observed near or at toe-off for the other degrees of freedom (i.e., knee and hip), but would not be considered 'clinically' or practically meaningful.

DISCUSSION: With the use of this analysis tool, it was possible to detect important, but subtle mechanical abnormalities with minimal statistical training through the use of a colour map. Therein, the patient being assessed presented with left-sided medial compartment knee pain, however the analysis tool identified the patient's largest mechanical abnormality located at the ankle joint of his right unaffected limb. If not identified using a holistic SPM approach, and a treatment plan implemented, it is plausible this mechanical compensation strategy would lead to a musculoskeletal overuse injury to the patient's right ankle plantarflexors.

These findings highlight the objective sensetivitiy of SPM for exploratory gait analyses as the abnormal gait mechanics to the contralateral limb may have been missed using traditional analysis methods. Therein, it is plausible that clinical researchers would have logically focused their attention on the left limb, which is where the patient was presenting with medial compartment knee pain. Future research is recommended to investigate whether this magnitude of statistical effect analysis tool would: 1) be used by gait researchers and clinicians, 2) provides unique insights' to treatment pathways and/or 3) improve rater reliability.

CONCLUSION: We have built and tested a user-friendly human movement analysis tool capable of calculating time varying magnitudes of statistical effect at both the three-component vector level (3D joint moment) and one-component scalar level (i.e., flexion/extension, abduction/adduction and internal/external rotation joint moments). Once complete, the magnitude of statistical effect analysis tool will be made freely available for download from the time varying statistical package SPM1D (spm1d.org).

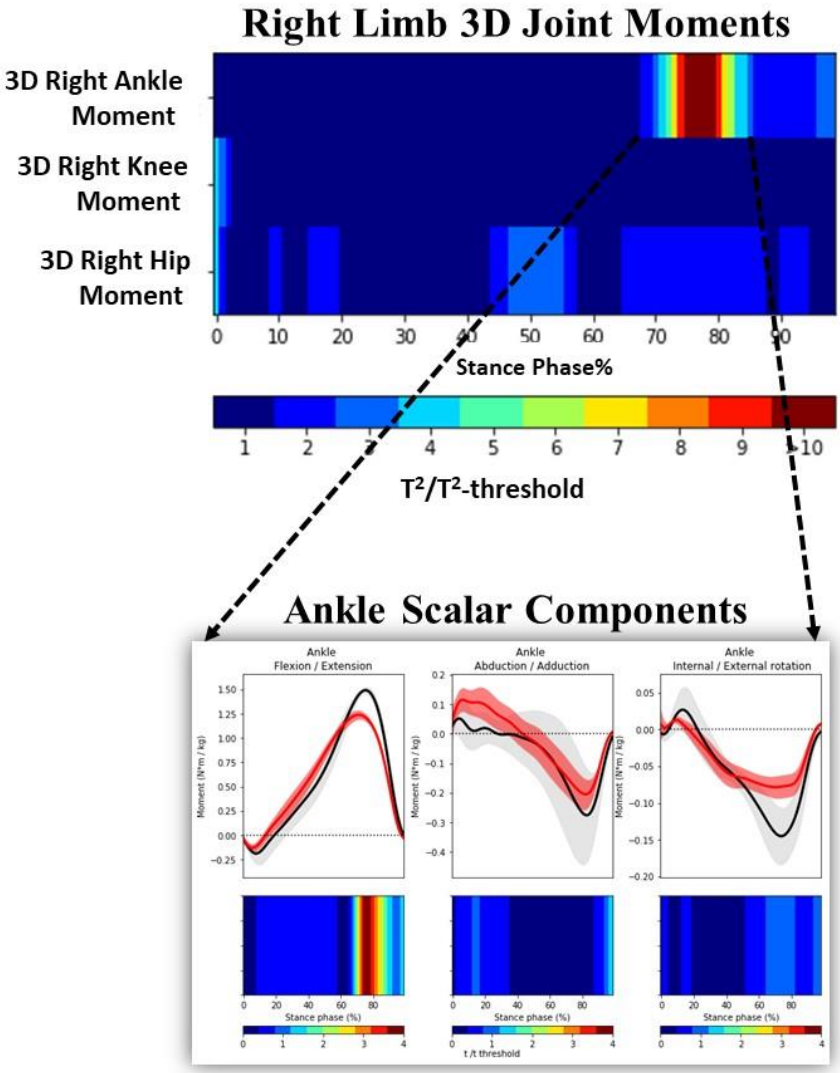

Figure 3: SPM magnitude of statistical effect colour map for joint moments of the right limb. The top pane is a depiction of a 3D vector analysis for all three joints of the right limb. The bottom pane represents scalar components of the 3D ankle joint vector. The colour blue represents no/minimal effect and dark red represents large/maximum effect.

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