Motion-based Phenotypes of Healthy and Chronic Low Back Pain Individuals Using High Deflection Strain Gauges

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INTRODUCTION: Chronic low back pain (cLBP) is a condition that negatively impacts millions of people worldwide. Although most cLBP patients exhibit similar symptoms, the underlying causes are multifactorial and treatments that work for one person will not necessarily work for another. Previous published work has shown that spinal biomechanics is sensitive to both anatomical defects and psychosocial conditions. Thus, it is plausible that motion-based phenotypes may reveal clusters that correspond to different cLBP etiologies which may also correspond with groups that may respond favorably to similar treatment options. The present work utilizes a recently developed wearable sensor system to provide high spatial resolution motion phenotypes of cLBP and control subjects, and to compare the patient-reported outcome data from these subjects to identify clinically relevant correlations.

METHODS: A cohort of 306 participants, between 35 and 65 years old, (150 control, 156 with cLBP) performed a specific set of 13 uniplanar and multiplanar movements during which their biomechanical data were recorded. Of the 150 control subjects 84 were male and 66 were female. There were 81 male and 75 female participants with cLBP. The subject testing was done in accordance with the approval of our institutional review board. All subjects also completed a survey that asked for demographic information (education level, employment, BMI, age, race, etc.) and patient reported outcomes (PROs) addressing a comprehensive evaluation of their biopsychosocial welfare (the BACPAC consortium common dataset [1]). Biomechanical data were recorded through the use of a wearable array of 16 nanocomposite high deflection strain gauges arranged across the skin of the lumbar region, which capture dynamic, high-resolution strain field data. The wearable sensor was applied to a participant's lower back using the L5 vertebra as a reference point. Once the array was placed on the participant, they were instructed to perform 6 repetitions of each of the different movements. Biosignal features from each of the 16 sensors for the last 4 repetitions were extracted and averaged.

Participants who were missing a substantial fraction of their biomechanical data due to sensor failure or data collection failure were excluded (86 subjects). A standard scaler was used to equally weight each biomechanical feature. Two datasets were considered in the following analysis: one only contained biomechanics data for the participants and the other contained demographic information in addition to the biomechanics data. The scaled and processed data were subjected to principal component analysis (PCA), where the number of PCA dimensions accounted for 80% of the variance. Agglomerative clustering was used to divide the subjects into phenotypes based on the PCA results. The resulting phenotypes were then compared to see how they correlated with participants with cLBP vs. without. The different phenotypes were also compared to see if they differed in different biopsychosocial categories.

RESULTS: The silhouette criterion was used to determine the optimal number of clusters for each of the two datasets. Based upon this, 4 clusters were chosen for the dataset consisting only of the biomechanics data and 5 clusters were chosen for the dataset consisting of the biomechanics with demographics data. Figure 1 shows the clustering results for the Biomechanics dataset in PCA space. Box and whisker plots were used to show correlations between the phenotypes and different PROs, as shown in Figure 2. A one-way ANOVA test was performed to determine the statistical significance of a relationship between phenotypes and the given PRO, and the resulting p-value is shown underneath each plot.

DISCUSSION: The results of this study show the ability to find different phenotypes based on movement and demographics. Correlations between these phenotypes and PROs were explored. Individuals with cLBP were mostly grouped into either Phenotype 1 or 2. Individuals with cLBP within Phenotype 2 showed a stronger relative psychosocial influence (PROMIS Depression and Pain Catastrophizing), for example. This could signify that while Phenotype 1's pain is caused by physical issues, Phenotype 2's pain could partially stem from biopsychosocial influences. One limitation of this study is the small sample size. Additional tests would need to be done on a larger number of participants to verify the validity of these phenotypes and improve upon them. Additionally, identifying the most impactful biomechanics features and simplifying the dataset could reduce noise and improve the clustering analysis.

SIGNIFICANCE/CLINICAL RELEVANCE: Distinct cLBP-related phenotypes were identified based solely on the principal components of their spinal motion characteristics. These phenotypes exhibited distinct and statistically significant differences in patient reported outcome data and may have future clinical relevance in identifying groups of people with chronic lower back pain who respond similarly to different types of clinical interventions.

REFERENCES: [1] Mauck, et al. (2023) *Pain Medicine*, 24(Supp 1):pnac202

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IMAGES AND TABLES:

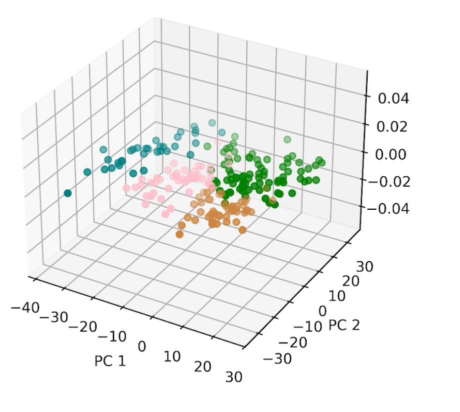

Figure 1: Three-dimensional visualization of the separation of the four most significant principal components.

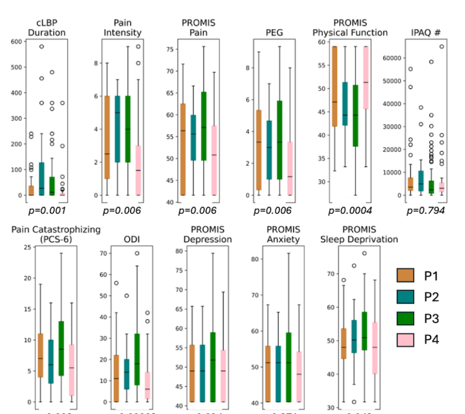

Figure 2: Patient-reported outcomes for each of the 4 cLBP phenotypes (P1, P2, P3, P4) demonstrate distinctive biopsychosocial characteristics.