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Variability and Complexity of Postural Control and Their Associations with Seated Discomfort.

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Abstract:

Sitting has become the most common work posture in todays society, and workstations requiring prolonged sitting are associated with seated discomfort. Discomfort has been identified as a precursor to pain and, as such, seated discomfort may, if sustained, lead to pain in the related body regions. Low back pain is the most common type of pain reported in adults, and pose a significant societal cost.

The variability of biological systems has been shown to change with pain and disease. This master thesis concerns the variability of seated postural control during the development of seated discomfort, by means of linear and nonlinear analysis techniques. Discomfort ratings, kinetic and kinematic data were sampled from 9 healthy, male subjects during prolonged sitting. Correlation analysis was performed to determine the correlation of each parameter to discomfort. Results showed that the amount of variability, was positively correlated to discomfort, whereas complexity was negatively correlated with discomfort, for all variables. These findings suggest that objective postural parameters are interrelated with subjective discomfort, and that the importance of the dynamics of seated posture may challenge the idea of a static ideal seated posture.

Contents

Preface

This master thesis was composed by group 1087a in the period from september 2nd 2008 to june 4th 2009 at the department of Health Science and Technology at Aalborg University. The theme for theproject was "Applied biomedical engineering and informatics". The supervisors for the project were Pascal Madeleine, Mark de Zee and Christian Gammelgaard Olesen.

The project consists of two parts; a scientific paper and worksheets supporting the paper. The appendix holds theoretical background for the methods applied and a review of the anatomy of the body regions pertaining to the experiment conducted.

Aalborg University, june 4th 2009

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Chapter 1

Introduction

Sitting has become the most common work posture in todays society, where three-quarters of all workers in industrialised countries are associated with a workplace that requires prolonged sitting (Lis et al. (1975)). Prolonged sitting in combination with awkward postures has been identified as a risk factor for the development of low back pain (LBP), which is the most common type of pain reported by adults (Sembrano and Polly (2009)), and is one of the most costly disorders for the working population worldwide (Lis et al. (1975)). In the UK the total costs of back pain was estimated to £10668 million in 1998, including care costs and production losses (Maniadakis and Gray (2000)). Discomfort has been identified as a precursor to pain (Madeleine et al. (1998)), and workstations requiring prolonged sitting (e.g. video display units (VDUs)) have been associated with infrequent postural changes and the presence of discomfort (Fenety and Walker (2002)). Infrequent postural changes influence the structures of the lower back and have been shown to be interrelated with discomfort (Corlett (2006)).

When the body is in neutral standing position, the shape of the hip capsule and the passive role of the hip flexors provide stability in the hip joints (Martini (2004)) (see appendix A for a review of the lumbo-pelvic anatomy). In this position, the pelvis is tilted anteriorly, providing an S-shape of the vertebral column, that minimises the back muscle activity required to maintain balance and minimises the load on the spine (Martini (2004)). Dynamical disc pressure is beneficial, as the discs gain nutrients from the pressure applied to them (Corlett (2006)). When going from a standing to a seated position, the location of the pelvis is shifted from neutral position to a backwards rotated position, aided by the hamstrings exerting a pull on the pelvis (Corlett (2006)). This fascilitates a kyphotic curvature of the lumbar division of the spine, which can be harmful to the structures of the spine, in that disc pressure is increased, as is the stress on ligamentous and articular structures (Claus et al. (2008)). Prolonged, static pressure causes the discs to creep and assume a more convex form at the rim. The discs may

rupture or produce more pressure to the nerves in the spinal column (Corlett (2006)).
Forward rotation of the pelvis will influence the shape of the lumbar spine, which will approach normal shape (Janssen-Potten et al. (2001)) and thereby reduce pressure on the discs. However, maintaining a lordotic lumbar curvature requires increased activity of the back muscles (Claus et al. (2008)). When muscles in the back contract, pressure is applied to the intervertebral discs. As such, a lordotic lumbar curvature is not necessarily better, as it, if sustained for longer periods of time, will also cause increased pressure on the intervertebral discs (Corlett (2006)). Lordosis has furthermore been shown by Vergara and Page (2002) to be positively correlated with lumbar pain, arguing that the negative effect is due to the muscular effort required to maintain lordosis. Thus, the literature offers no unequivocal recommendation for seated posture, and the associations between seated posture and discomfort are not yet fully understood.

Linear analyses have been widely used in both clinical and research settings, to assess the variability of system outputs. They describe the constant relationships between two variables and can be used to quantify the variability of a time series. Using linear analysis, Liao and Druru (2000) found a positive association between subjective discomfort ratings and the frequency of postural changes for subjects performing VDU work. Substantiating these results, Fenety and Walker (2002) showed that the frequency of postural shifts increased over time during VDU work, and Vergara and Page (2002) found the frequency and size of in-chair movements (ICM) to to be positively correlated to subjective discomfort ratings. However, over the last years, there has been a shift in the understanding of the nature of sitting. It is now recognized as a dynamic rather than a static task (Fenety et al. (2000)), and linear analyses do not provide a full overview of the changes in postural control, as changes can occur in the patterns of the system outputs, which are not detected by linear analysis. Non-linear analysis is a family of mathematical measures that provides spatio-temporal characteristics of a time series (Seely and Macklem (2004)). Entropy measures are part of the family of non-linear analysis techniques, and measure the randomness of a time series and indicates the regularity of the system(s) producing the output. Higher entropy means higher randomness and thus less regularity. Entropy is also interpreted as the rate of information generation and, as such, can be used to provide an estimate of the complexity of the underlying system producing the dynamics in question (Lipsitz and Goldberger (1992)). Advances in the field of non-linear analysis have revealed that the spatio-temporal dynamics of physiological systems can discern healthy from ill systems (Vaillancourt and Newell (2002)), yielding measures of complexity highly relevant for clinical applications.

The response of physiological systems dynamics to disease has been debated in the literature (Vaillancourt and Newell (2002);Lipsitz and Goldberger (1992)), studies indicating that the intrinsic dynamics of the system in question influences the direction of change in complexity. For systems with fixed point attractors, i.e. systems for which the output tends to return to the same value following perturbations, the complexity of the output tends to decrease due to

disease, whereas the opposite has been demonstrated to be the case for systems with oscillating intrinsic dynamics, i.e. systems for which the value that the output tends to return to after perturbations, varies over time (Vaillancourt and Newell (2002)). Studies on standing postural control show a strong tendency of complexity of related physiological signals being negatively associated with disease (Vaillancourt and Newell (2002)). Also, low back pain has been shown to be associated with a decrease in complexity of electromyographic activity of the lower back muscles (Sung et al. (2007)). Research into the non-linear dynamics of seated postural control may lead to a deeper understanding of the mechanisms involved in seated discomfort.

Postural changes may be assessed by analyzing the trajectory of the center of pressure (COP), as postural changes result in changes in the body center of gravity (COG), which reflect in the body COP. COP trajectories provide a picture of the collective outcome of the postural control system, and as such, analysis of these signals may reveal aspects of the integration of the motor control systems interacting to control posture. Furthermore, the importance of lumbar curvature in relation to the development of discomfort and pain has previously been demonstrated. LBP has been shown by Volker (1991) to be related to lumbar curvature, and increased discomfort in the lumbar region has been found to be the main cause for increases in general discomfort in the seated position (Vergara and Page (2002)). The lack of consistency in the literature regarding optimal lumbar posture, together with the recognition of sitting as a dynamic task, motivates the further investigation of the variability of lumbar curvature to seated discomfort.

The focus of the present study was to evaluate the dynamics of COP and lumbar curvature as indicators of subjective seated discomfort during prolonged sitting, using both linear and non-linear analysis techniques. Based on previous findings, we hypothesize that an increase in discomfort is related to an increase in the amount of variability and a decrease in the complexity of COP and of lumbar curvature displacement. Also, we expect discomfort to be associated with a backwards rotation of the pelvis.

Chapter 2

Methods and materials

The purpose of the present project was to measure the responses of the body to prolonged sitting, in order to detemine possible correlations between subjective, seated discomfort and the variability of postural control output signals. To do so, we exposed healthy subjects to a prolonged sitting task, while measuring COP and lumbar curvature and collecting subjective discomfort ratings.
This chapter describes the considerations leading to the experimental setup and summarizes these in an experimental protocol. Theoretical background for the applied methods is described in appendices B to G, and references are made to these appendices throughout this and subsequent chapter.

2.1 Experimental setup

Previous studies on seated discomfort typically pertain to specific seating arrangements and/or specific tasks. Differences in experimental setup complicate comparisons of results between studies using different protocols, as it is not always possible to discern discomfort arising from the sitting task and from possible work tasks. Also, the presence and type of backrests, armrests, cushions, etc. is likely to influence the development and perception of discomfort in incalculable ways. To gain scientific certainty in our claims regarding the correlations between perceived discomfort and the variables under investigation, it was imperative that the perceived discomfort arose from the act of sitting itself. As such, subjects were seated on an elevated, horizontal surface constituting the seat pan, with no cushion, back-, arm- or footsupport provided.
A force platform was used as a seat pan to provide kinetic data for the assessment of COP trajectories. The anterior edge of the force platform was padded to minimize discomfort arising from resting the popliteal area against the sharp edge, as this was not considered as directly

related to the act of sitting. Kinematic motion capture using reflective markers was used to determine the position of anatomical landmarks for the calculation of lumbar curvature.

2.2 Procedure

The literature offers no reasoning for the choice of duration of sitting tasks when assessing biomechanical responses to seated posture. Intervals vary consistently between approximately 30 minutes and two hours. Also, there are no national guidelines in Denmark for the maxiumum duration of seated work. For the present project, it was essential that subjects sat long enough to experience discomfort. To ensure that the experiment yielded the data required, pilot experiments were conducted to establish the duration of the sitting required for the subjects to develop discomfort. These experiments indicated that 90 minutes was sufficient to reach an adequate discomfort level. Legs and feet of the subjects were required to remain at rest during measurements, as e.g. swinging of the legs were considered to be boredom-related rather than related to seated discomfort. To prevent lack of circulation in the legs, breaks of 20 seconds were inserted after every 5 minutes of kinetic and kinematic measurements, to allow movement of the legs to ensure bloood circulation. The breaks were utilized to perform subjective discomfort ratings pertaining to the interval immediately prior to the break. Figure 2.1 illustrates the course of the experimental session, with 18 intervals of 5 minutes each, providing a total duration of the sitting task of 96 minutes including the breaks..

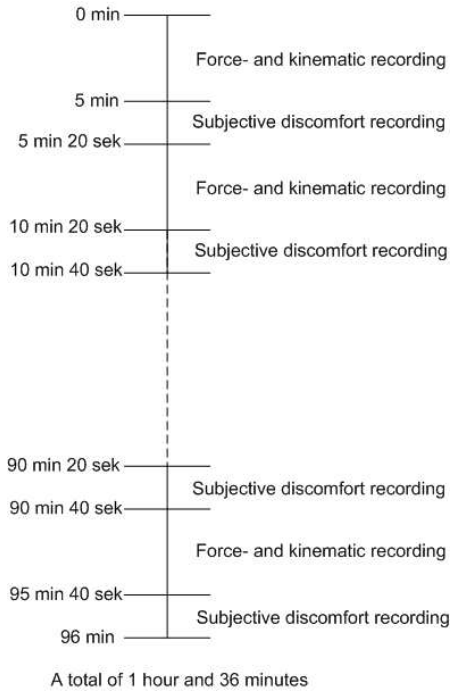

Figure 2.1: Time line for data recording.

During the experiment, subjects watched a film, "The United States of Leland", to pass time. The local Ethics Committe has approved the experimental setup and procedure.

2.3 Subjects

As postural responses to sitting has been shown to vary between genders (Dunk and Callaghan (2005)), only male subjects were recruited, and the group of subjects was sought to be as homogenous as possible to minimize the risk of generating results that could be ascribed to anthropometric differences. Subjects were recruited based on the following inclusion and exclusion criteria:

Inclusion criteria

- Male
- 180-195 cm of height
- 20-30 years of age

Exclusion criteria

- Body Mass Index (BMI) <20 or >25

- History of back pain
- Spinal deformities

12 subjects were recruited, but three subjects were excluded during the course of the experiment. For one subject, the motion capture system crashed near the ending of the experiment. For the other, the quality of the kinematic recording made it impossible to retrieve reliable data from the records. Finally, the third subject experienced pain from the sitting task, making the experimental results unfit for analysis of discomfort.
The data of the remaining nine subjects were as follows (mean(SD)):

- Weight (kg):79,4(6,9)
- Height (cm):186,8(4,8)
- BMI: 22,7(1,5)
- Age (yrs):24,8(1,6)

2.4 Data recording

Every 5 minutes, during the 20 second break, Body Part Discomfort (BPD) ratings were collected according to appendix B, using a 6 level scale from 0 to 5, 0 representing "no discomfort" and 5 representing "worst imaginable discomfort". Each subject was presented with an illustration of the human body segmented into 9 different body parts, and was asked to rate his level of discomfort.
Previous studies investigating the non-linear dynamics of COP trajectories have used sampling frequencies ranging from 2,4 Hz (Hermann (2005)), 20 Hz (Duarte and Sternad (2008)Doyle et al. (2004)), 100 Hz (Haddad et al. (2008);Cavanaugh et al. (2007);Donker et al. (2007);Donker et al. (2008);Sabatini (2000);Schmit et al. (2005);Schmit et al. (2006)), to 960 Hz (Harbourne and Stergiou (2003)). In the present study, reaction forces and moments were sampled at a rate of 100 Hz from an AMTI OR6-7 1000 force platform (seat pan) with a gain of 4000. Kinematic data was likewise sampled at a rate of 100 Hz by use of the Qualisys Proreflex 240 Camera System (Qualisys, Gothenburg, Sweden) (see appendix C).

2.5 Data analysis

BPD scores for each subject were summed for each interval, providing a BPD index, as described in appendix B.
Force platform data were transformed to COP coordinates using MATLAB (Mathworks, Natick, MA), according to appendiks D. Both the medial-lateral and anterior-posterior component of the COP data were analysed.
Kinematic lumbar curvature data were processed using Qualisys Track Manager (QTM) software and was exported to MATLAB and transformed to lumbar curvature according to the method described in appendix E. Negative values denoted kyphotic curvatures and positive values denoted lordotic curvatures. Mean of each variable was calculated to provide an indication of the overall shift in posture during the development of discomfort.
To assess the linear characteristics of the signals, standard deviation (SD) was calculated as an indicator of the amount of variability. Also, the ICM frequency was calculated according to appendix E.5 for the lumbar curvature for each of the 18 intervals, to provide an alternate view on the changes in the amount of variability observed for lumbar movement.
Non-linear characteristics were assessed by employing sample entropy (SaEn), based on the discussion presented in appendix F (describing non-linear entropy analysis). Entropy quantifies regularity in a data series by assessing the probability that sequences of length m that are similar will remain similar when incrementing the length of the sequences to $m+1$. The similarity condition is determined by the tolerance, r. Output is a unitless, non-negative number where higher values indicate more complex data series. For a detailed mathemathical derivation of the formulas, see Richman and Moorman (2000). The embedding dimension, m, was chosen as 2, and the tolerance, r, was chosen to 0.1 times the standard deviation of the data series, in accordance with the recommendations of Pincus (1991b).
All data analysis was performed using MATLAB.

2.5.1 Statistical analysis

To associate changes in the dynamics of postural control to perceived discomfort, statistical analysis were performed. To determine the appropriate statistical analysis, data distribution analysis was performed. Results indicated that the data were suited to undergo multiple linear regression analysis. The process and results of the data distribution analysis is described in appendix G.
Multiple linear regression analysis was employed, with BPD index as the dependent variable and mean of medial-lateral COP component, mean of anterior-posterior COP component, mean of lumbar curvature, sample entropy of medial-lateral COP component, sample entropy of anterior-posterior COP component, sample entropy of lumbar curvature, standard deviation

of medial-lateral COP component, standard deviation of anterior-posterior COP component, standard deviation of lumbar curvature and lumbar in-chair movement frequency as predictor variables. All statistical analyses were performed using SPSS version 16.0 (Chicago, IL, USA). $p<0.05$ was considered as significant.

2.6 Experimental protocol

Based on the preceding considerations, the experimental sessions were conducted as follows.
Before subject arrival

- Motion capture system was calibrated
- The force platform was connected to the computer through an amplifier
- Amplifier gain was set to 4000
- Hardware low pass filter was set to 10.5 Hz
- Amplifier offset was set to zero

Upon subject arrival

- Subject's weight and hight were measured
- Subject was asked about any history of back pain
- Subject was briefed on the experimental procedure, including the use of the BPD scale
- Subject was asked to sign a written consent
- Three markers were placed on the lumbar spine and one on the sternum, according to appendix E.

Measurements
Data collection from motion capture system and force data was startet. Every 5 minutes, kinetic and kinematic recordings were suspended, and subjects were handed the discomfort rating figure presented in appendix B. They were asked to first assess the region in which they were experiencing the most discomfort, then the region with the second-most discomfort and so on through all regions. Discomfort ratings were noted in a scheme by the examiner. After assessing all body parts, subjects were allowed to move their feet and lower legs while seated, to provide for blood circulation. All other movement than that of the legs and feet was explicitly prohibited during the breaks to prevent responses to discomfort to take place outside of the recordings. The procedure was repeated for a total of 18 times.

Chapter 3

Results

In this chapter we present the data from the experiment and test for correlations of each variable with time and with discomfort. Table 3.1 summarizes the data sets obtained from the experiment and lists the abbreviations used throughout this and subsequent chapters.

Body Part Discomfort index	BPD
Mean medial-lateral COP component	ML mean
Medial-lateral COP standard deviation	ML SD
Medial-lateral COP sample entropy	ML SaEn
Mean anterior-posterior COP component	AP mean
Anterior-posterior COP standard deviation	AP SD
Anterior-posterior COP sample entropy	AP SaEn
Mean lumbar curvature	LC mean
Lumbar curvature standard deviation	LC SD
Lumbar curvature sample entropy	LC SaEn
In-chair movement frequency	ICM

Table 3.1: Data sets obtained from the experiment and appurtenant abbreviations.

3.1 Correlations with time

The data distribution analysis described in appendix G yielded the data suitable for regression analysis. After visually examining each data set as a function of time, a regression equation corresponding to the shape of the data distribution was employed. We used the SSE and R-square values to determine the goodness of fit of each regression. SSE is the sum of squares due to error and measures the total deviation of the measured values from the corresponding values of the fit. Thus, the closer SSE is to 0, the better the fit.

The R-square value estimates the proportion of the variation in the data set that can be ascribed to the regression model used. Thus, the closer the R-square is to 1, the better the fit. When employing linear regression, and the resulting goodness of fit statistics warrent examination of regression equations of more coefficients, the adjusted R-square value is evaluated instead of the R-square value, as it takes into account the residual degrees of freedom and is considered the best indicator of the fit when comparing models which add coefficients to the previous model. The absolute value of these goodness of fit statistics are viewed primarily comparatively to determine whether increasing the number of coefficients in a polynomial regression equation or some other type of regression equation yields a better fit than a linear one. Finally, we used the p-value to establish the validity of the fit. If this was below 0.05, the fit was considered valid.

No data sets exhibited significantly better fits than linear. Table 3.2 lists the Pearson coefficients and p-values of the linear regressions.

Parameter	Pearson coefficient	P-value
BPD	0.666	<0.001**
ML mean	0.035	0.330
ML SD	0.362	<0.001**
ML SaEn	-0.471	<0.001**
AP mean	0.203	0.005**
AP SD	0.310	<0.001**
AP SaEn	-0.218	0.003**
LC mean	0.200	0.005**
LC SD	0.268	<0.001**
LC SaEn	-0.207	0.004**
ICM	0.296	<0.001**

Table 3.2: Pearson coefficients and p-values of linear regression equations over time for all data sets. Parameters marked with '*' or '**' were statistically signifcantly correlated with time with a significance level of 0.05 and 0.01, respectively.

The Pearson coefficient is a measure of the linear dependency between variables and indicates the strength and direction of the correlation. A negative Pearson coefficient denotes a negative linear relationship and vice versa. The absolute value of the Pearson coefficient lies between 0 and 1, with 0 indicating no correlation between variables and 1 indicating perfect correlation. The p-value indicates whether the correlation is statistically significant. Values below 0.05 indicate statistical significance of the fit.

Figures 3.1, 3.2 and 3.3 illustrate the tendencies of the assessed parameters over time. Each color refers to a specific subject, and the red lines illustrate linear regression of the data sets. BPD increased significantly over time (figure 3.1), and the buttocks and the lower back accounted for app. 43% of the recorded discomfort. Mean of the anterior-posterior COP component (figure 3.2a) and mean lumbar curvature increased significantly over time (figure 3.2c), while

mean of the medial-lateral COP component (figure 3.2b) did not change significantly. Results showed a statistically significant increase in the amount of variability for both anterior-posterior and medial-lateral COP components (figures 3.2d and e), lumbar curvature (figure 3.2f) and ICM frequency (figure 3.3). Complexity decreased over time for all investigated variables, as expressed by a statistically significant decrease in sample entropy (figure 3.2g, h and i).

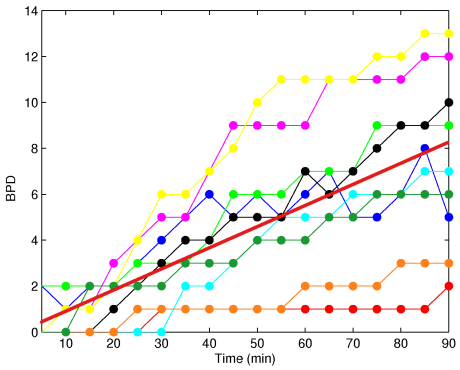

Figure 3.1: Body part discomfort index. Each color represents one specific subject. The red line illustrates the linear regression of the data set.

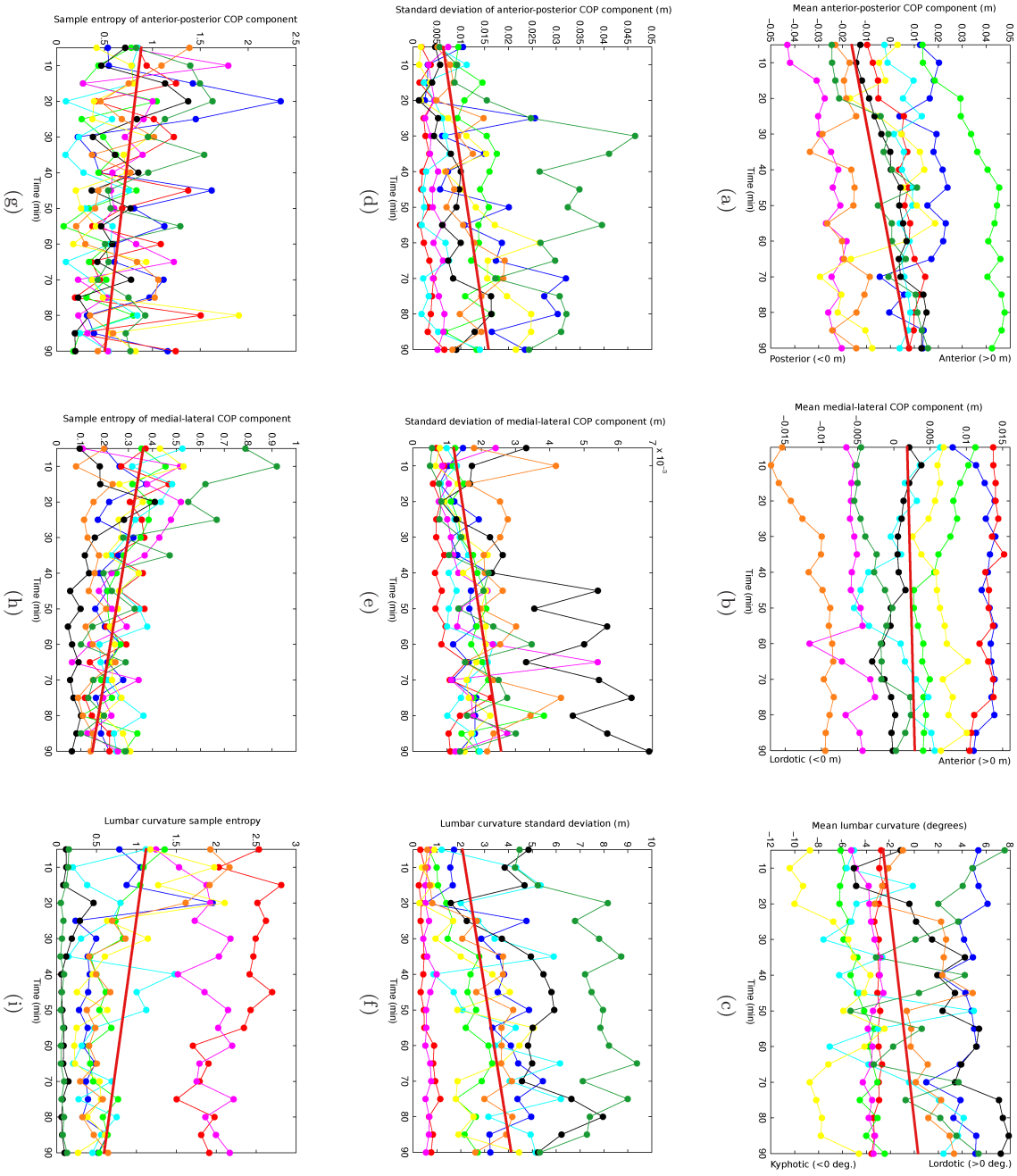

Figure 3.2: Mean (top row), standard deviation (middle row) and sample entropy (bottom row) of anterior-posterior (left column) and medial-lateral (middle column) center of pressure components and lumbar curvature (right column). Each color represents one specific subject. The red line illustrates the linear regression of each data set.

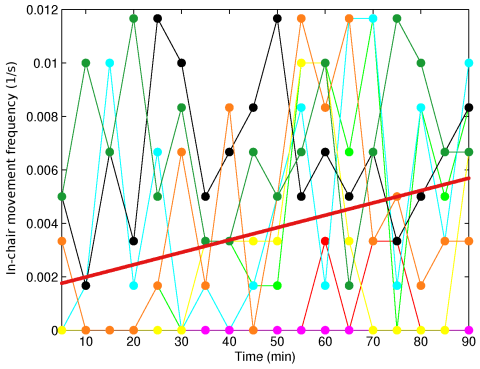

Figure 3.3: Lumbar curvature in-chair movement frequency. Each color represents one specific subject. The red line illustrates the linear regression of the data set.

3.2 Correlations between variables

Correlations between variables were tested using multiple regression with BPD as the dependent variable and with ML mean, ML SD, ML SaEn, AP mean, AP SD, AP SaEn, LC Mean, LC SD, LC SaEn and ICM as independent variables. Table 3.3 lists the results of the regression. The table lists the Pearson correlation coefficients, and statistically significant correlations are marked with '*' if significant with a significance level of 0.05 and with '**' if significant with a significance level of 0.01.

There were statistically significant correlations between BPD and all predictor variables besides LC mean, ML mean and AP mean. SD was positively correlated with BPD for all parameters. Also, ICM was positively correlated with BPD, substantiating the indication of increased amount of variability with increased discomfort. SaEn was negatively correlated with BPD for all parameters.

Pearson											
	BPD	MLmean	APmean	LCmean	MLSaEn	APSaEn	MLSD	APSD	LCSD	LCSaEn	ICM
BPD	1	-	-	-	-	-	-	-	-	-	-
MLmean	0.029	1	-	-	-	-	-	-	-	-	-
APmean	0.125	0.541**	1	-	-	-	-	-	-	-	-
LCmean	-0.016	-0-091	0.065	1	-	-	-	-	-	-	-
MLSaEn	-0.278**	0.091	-0.120	-0.200**	1	-	-	-	-	-	-
APSaEn	-0.271**	-0.070	-0.235**	0.128	0.098	1	-	-	-	-	-
MLSD	0.329**	-0.313**	0.052	0.361**	-0.696**	-0.134*	1	-	-	-	-
APSD	0.273**	0.003	0.158*	0.171*	-0.151*	0.097	0.163*	1	-	-	-
LCSD	0.140*	-0.139*	0.139*	0.480**	-0.162*	-0.033	0.357**	0.675**	1	-	-
LCSaEn	-0.193**	0.113	-0.252**	-0.392**	0.166*	0.116	-0.368**	-0.565**	-0.823**	1	-
ICM	0.133*	-0.108	0.205**	0.408**	-0.123	-0.121	0.263**	0.379**	0.637**	-0.621**	1

Table 3.3: Pearson correlation coefficient as calculated from multiple regression. Parameters marked with '*' or '**' are significantly linearly correlated with a significance level of 0.05 and 0.01, respectively

The predictor variables included accounts for 27.5 % of the variance of BPD, expressed by an R-square value of 0,275 for the multiple regression. The p-value is <0.001, indicating a statistically significant model.

Chapter 4

Discussion

The hypothesis motivating the present study stated that the complexity of COP and of lumbar curvature should decrease with increased discomfort, while the amount of variability should increase. Also, it suggested a negative association between discomfort and lumbar curvature. The results supported the first part of the hypothesis, i.e. in the presence of discomfort, the entropy of the COP variations decreased, indicating more regular and less complex movements. Entropy of the lumbar curvature showed the same tendency to decrease with increasing discomfort. Also, the results showed positive relationships between discomfort and amount of variability for both COP trajectories and changes in lumbar curvature. Conversely, the results did not confirm the second part of the hypothesis that lumbar curvature should decrease in the presence of discomfort.
In this chapter, we first discuss the methods applied in the present study. Hereafter, we proceed to discuss the findings of the project and their implications.

4.1 Methodological considerations

In this section, we review our methods and experimental design and compare our results to those of previous studies to establish the validity of our data and to approximate the consequences of our choice of methods on the results of the study. It has not been possible to identify studies with methodologies comparable to those of the present study, and therefore, absolute values obtained from the present study can not be validated by such means. Validation is thus done through comparing tendencies of the data with those observed in previous studies.
The method of measurement of lumbar curvature was modified from a technique for assessing lumbar curvature in radiographic images. This leaves room for inaccuracies in terms of palpation of the anatomical landmarks and the markers moving independently of the vertebrae

because of their attachment to the skin. We sought to minimize inaccuracies through consulting a chiropractor with thorough knowledge of the structures of the spine to acquire experience with palpating the landmarks through skilled supervision.

Throughout the experiment, subjects repeatedly expressed the need for additional levels on the discomfort scale to express their level of discomfort more accurately. As such, when inquiring whether they were allowed to answer in half steps on the scale, which was not allowed, they most oftenly chose the nearest lower value. As such, it might have proven better to use a scale with a wider range, allowing for more differentiation between intervals. This might have resulted in larger variations in BPD, even in the first intervals and thus could have influenced the homoskedasticity and the results of the normality tests for the BPD data. However, as BPD is a frequently used, acknowledged method of ranking subjective discomfort, using this method is consistent with best practice in this field.

4.1.1 Experimental setup

In previous studies on seated discomfort, the experimental setup was typically directed towards some specific application, e.g. discomfort during driving (Hermann (2005);Hermann and Bubb (2007)) or in relation to specific chair designs (Vergara and Page (2002);Volker (1991)) or work tasks (Starr et al. (1985)). The drawback of this approach is the difficulty to discern the factors interacting with the perception of discomfort, i.e. whether it is associated to the sitting task itself, or whether it is associated with e.g. the work task. Furthermore, the presence/absence of backrest and armrests, etc., complicates comparisons between studies.
The aim of the experimental setup of the present study was to eliminate all unnecessary factors that might interact with the perception of discomfort, so that the discomfort perceived by the subjects was exclusively associated with *sitting*. As such, we omitted backrest, footsupport, armrests and cushion and padded the front edge of the force platform to avoid discomfort in the popliteal area. Also, it was imperative, in order to answer our hypothesis, to provoke a response of discomfort. Pilot studies showed that this respons was delayed markedly by using a cushion. In our setup, the influence of external factors on the subjects' perceived discomfort is minimized, gaining scientific certainty in our claims regarding the correlations between perceived discomfort and the variables under investigation. However, the setup has less direct clinical relevance, as the seating arrangement is far from any real seating arrangement used in practice.

4.1.2 Postural variability measures as indicators of seated discomfort

The present study presents the correlations of subjective seated discomfort to mean posture, amount of variability and complexity of center of pressure trajectories and lumbar curvature. The predominance of discomfort observed in the back and under the buttocks confirms that the variables under investigation are in fact probable as indicators of seated discomfort.

Regarding mean posture, the hypothesis of the present study suggested a decrease in lumbar curvature to be associated with an increase in discomfort. To test this hypothesis, the mean for each of the 18 intervals was calculated (see figure 3.2(c)). Regression analysis showed that mean lumbar curvature was not significantly correlated with discomfort. This procedure was repeated for each center of pressure component (anterior-posterior and medial-lateral direction, see figures 3.2(a) and (b), respectively) to further explore the associations of discomfort with global postural changes. Neither medial-lateral or anterior-posterior mean center of pressure component, nor mean lumbar curvature, showed any correlations with discomfort. These results suggest that mean posture variables do not provide an objective way to assess discomfort development.

The hypothesis also suggested that the amount of variability of both lumbar curvature and center of pressure displacement is positively correlated with discomfort. As figures 3.2(d), (e) and (f) illustrate, the standard deviation of all three variables did indeed increase over time, and as expressed in table 3.3, all showed statistically significant positive correlations with discomfort. In-chair movement frequency indicates the number of changes between kyphotic and lordotic postures (i.e. an indication of macromovements), whereas the standard deviation of the lumbar curvature denotes the *size* of the lumbar movements. In-chair movement frequency likewise increased over time (see figure 3.3) and showed statistically significant positive correlations with discomfort. The increase in standard deviation of center of pressure components and in in-chair movement frequency over time all illustrate an increase in the amount of variability. Gross medial-lateral center of pressure displacements are interpreted as a means of pressure relief of the gluteal region, as the peak pressure is lifted from either side. The increase in standard deviation with increased discomfort indicates a progressively larger need for greater/more effective pressure relief of the soft tissue under the buttocks, indicating associations between prolonged tissue pressure under the buttocks and discomfort. Given the lumbar-pelvic anatomy, with the shape of the spine closely intertwining with the tilt of the pelvis, the anterior-posterior center of pressure displacements are related to the variations in lumbar curvature, which is substantiated by the positive correlation observed between standard deviation of the lumbar curvature and standard deviation of anterior-posterior center of pressure displacement. Gross displacements of the lumbar curvature are likewise interpreted as a means of pressure relief, as changes in lumbar curvature rotates the pelvis and thus shift the location of the ischial tuberosities under the buttocks. Also, it may provide muscle- and ligamentous tension relief of the lumbo-pelvic

and gluteal body regions.
Previous studies on postural dynamics have shown a similar tendency as observed in the present study, i.e. increases in the amount of variability.Madeleine and Madsen (2009) studied the effects of work experience and neck-shoulder discomfort on work performance in meat industry workers, in terms of work cycle duration and kinematic displacement variables, and showed that the presence of discomfort was associated with an increase in the standard deviation of the vertical elbow-hip displacement. Other conditions have similarly been shown to increase the amount of variability, i.e. the study of Roerdink et al. (2006) revealed a decrease in COP standard deviation with rehabilitation of patients after a stroke, Donker et al. (2008) showed a greater amount of sway in children suffering from cerebral palsy than in typically developing children, and Schmit et al. (2006) demonstrated a COP path length for parkinson patients significantly greater than that for healthy controls.

A decrease was observed in sample entropy over time for all three parameters, i.e. anterior-posterior and medial-lateral center of pressure components and lumbar curvature (see figures 3.2(g), (h) and (i), respectively), along with significant negative correlations of sample entropy to discomfort (see table 3.3). Comparison with other studies on changes in complexity is complicated, as the direction of change is related to both the intrinsic dynamics of the system in question and the type of condition causing the change in dynamics (Vaillancourt and Newell (2002)). However, there is a tendency for the postural control system to exhibit decreased complexity in the presence of pain or disease (Sung et al. (2007);Vaillancourt and Newell (2002)). Our results suggest that the intrinsic dynamics of seated postural control correspond with those of standing postural control, which are generally perceived as fluctuating around an equilibrium point (Collins and De Luca (1993)). Collectively, these results of the present study indicate that seated postural control has a fixed point intrinsic dynamic, and that discomfort affects this type of dynamic in similar ways as does pain and disease.

4.1.3 Optimal seated posture

When the body is in neutral position, minimal strain is on the vertebrae. Postures oriented outside the neutral position may lead to increased muscle activity, discomfort and/or pain in the related body parts (Corlett (2006)). When muscles in the back contract, pressure is applied to the intervertebral discs (Corlett (2006)). Dynamical muscle activity is beneficial, as the discs gain nutrients from the pressure applied to them. Conversely, static activity can be harmful to the structures of the spine, in that when pressure is applied to the vertebrae, the discs creep and assume a more convex form at the rim. The discs may rupture and produce more pressure to the nerves in the spinal column. (Corlett (2006)) As such, lumbar curvature has been frequently used to define the most optimal seated posture. The literature offers contradicting recommendations for optimal seated posture with regards to lumbar curvature.Sanders and

Ernest (1992) proposed a seated posture similar to that of the upright posture to be most ideal, based on physiological aspects of sitting, as a kyphotic lumbar curvature results in increased disc pressure. Conversely, Claus et al. (2008) questioned a lordotic posture to be the "ideal" sitting posture, in that a lordotic lumbar posture requires more muscle activity than kyphotic postures.Vergara and Page (2002) stated the necessity of varying the posture, in that some postures may be helpful in short periods but harmful in long terms. Though it requires more muscle activity to maintain a lordotic curvature than to maintain kyphosis, which, for prolonged sitting, may induce muscle fatigue, maintaining kyphotic curvatures elevate the intervertebral disc pressure and may cause stress to the ligaments that are stretched in this posture (Corlett (2006)). The results of the present study may aid to explain the contradicting results in the literature on the subject of optimal sitting posture. Focus is most often on specifying some specific of curvature that is least harmful, when in fact, as our results suggest, it is not the *value* of the lumbar curvature, but the *variation* in the lumbar curvature that is associated with discomfort. Our results also support the statement made by Vergara and Page (2002) that some postures are harmful if sustained for a long period, in that we view the increased variability of lumbar curvature as a means to relieve discomfort, arguing that seated discomfort is a pre-stage to damage to the anatomical structures involved in sitting.

The correlations between discomfort and standard deviation of lumbar curvature and in-chair movement frequency substantiate the notion that the posture itself is not as good a predictor of discomfort as is *variation* of the seated posture. This is substantiated by the lack of correlation between discomfort and mean center of pressure components and lumbar curvature, and also by the significant positive correlations of discomfort to the amount of variability and complexity of center of pressure components and lumbar curvature.

In conclusion, the present study proposes associations between subjective seated discomfort and the amount and complexity of center of pressure and lumbar curvature variability. Results show that as discomfort increases, movement patterns become more regular, and larger and more frequent movements are observed, but no effect was observed for mean posture variables. Further research is needed into the physiological mechanisms involved in the observed decrease in complexity of the postural control system, in order to provide a more complete understanding of the dynamics of seated discomfort, which may have implications for the recommendations for ideal seated posture based on mean posture.

Part I

Appendix

Appendix A

Anatomy of the spine and lumbo-pelvic region

The primary anatomical regions involved in sitting are the gluteal and pelvic regions and the vertebral column. Bones, ligaments, muscles and other soft tissue structures take part in upholding seated posture. This appendix reviews the anatomy of these areas.

A.1 The gluteal region

The gluteal region includes the skin and fascia of the buttocks, and the appurtenant muscles and bones (Schilling and Wechsler (1986)). The buttocks are formed by the gluteal muscles, which are arranged in three layers; the superficial gluteus maximus, the intermediate gluteus medius, and the deep gluteus minimus, which cover the back of each pelvic bone and span the hip joint to be attached to the thigh bone (Schilling and Wechsler (1986)). The organization of the gluteal muscles is depicted in figure A.1

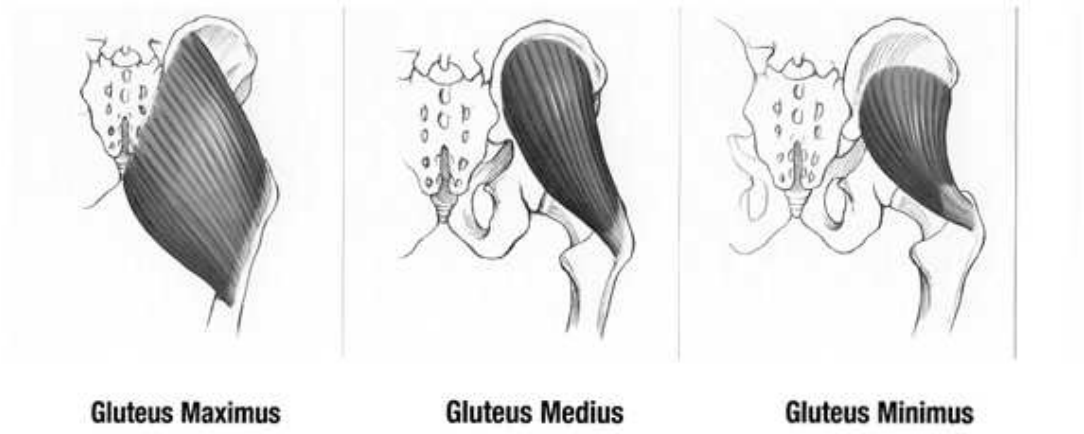

Figure A.1: Illustration of the organization of the gluteal muscles into superficial, intermediate and deep muscle layers. Illustration from `http://www.posetech.com/training/images/glutes.gif`

The primary actions of the gluteus maxima are extension and lateral rotation at hip, while the main actions for the two other gluteal muscles are abduction and medial rotation at the hip.(Martini (2004))

A.2 The pelvic region

The major bony structure in the gluteal region is the pelvis, which is formed by three bones; the hipbones (ossa coxae) and the triangular shaped sacrum (fusion of five vertebrae). These bones make up the pelvic girdle. The hipbones are each formed by the fusion of three bones; ilium, pubis and ischium (A, D and F in figure A.2, respectively). The superior most curved border of the ilium is the iliac crest (the most prominent bone in the buttock). The hipbones are connected anteriorly by the pubic symphysis (E in figure A.2). Posteriorly the hipbones are connected to the sacrum, through the sacroiliac joints (B in figure A.2). The pelvis is connected to the upper body through the sacrum which is a part of the spinal column, and to the lower body through the thigh bones through the acetabulum (C in figure A.2).(Martini (2004))

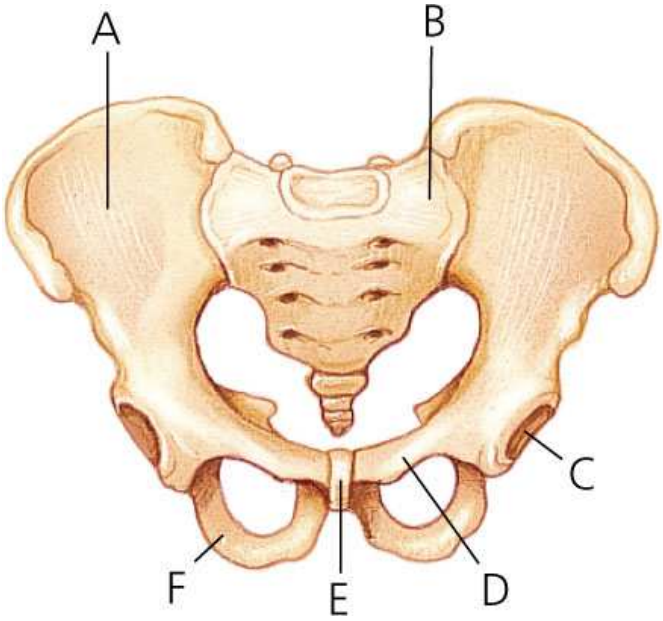

Figure A.2: Illustration of the pelvis. A: Ilium B: Sacroiliac joint C: Acetabulum D: Pubis E: Pubic symphysis F: Ischium. Illustration from `http://dirtmag.co.uk/images/uploads/news/A4pelvisBIG.jpg`

A.3 The vertebral column

The vertebral column is composed of seven cervical, 12 thoracic, five lumbar, five fused sacral vertebrae and the coccyx. The healthy vertebral column has an S-shaped form with a lordotic curvature of the cervical and lumbar divisions and a kyphotic curvature of the thoracic and sacral/coccygeal divisions, as illustrated in figure A.3

Figure A.3: The vertebral column, divided into cervical, thoracic, lumbar and sacral divisions. Illustration from `http://www.espine.com/Secondary-anatomy/spine.gif`

The size of the vertebrae varies throughout these divisions, as the forces of weightbearing increase from the cervical to the lumbar region. Thus, the vertebrae in the lumbar region are bigger than those in the cervical region.(Marcus (2004))
Figure A.4 illustrates a lumbar vertebra. The spinous process is externally palpable, which is utilized in determining the angle of lumbar curvature (see appendix E).

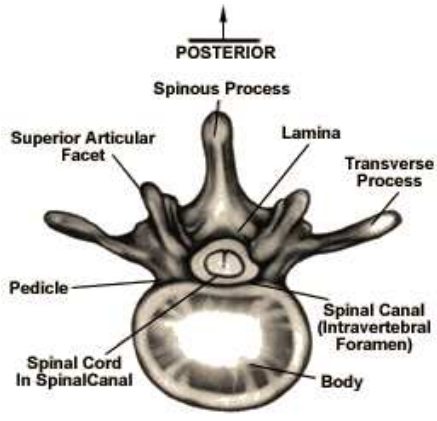

Figure A.4: Superior view of a lumbar vertebra. Illustration from `http://www.espine.com/Secondary-anatomy/verterbra.gif`

The main movements of the spine are extension, flexion, lateral flexion and rotation, which are all combined by movement of several segments. Extension of the spine results in an lordotic curvature, while flexion results in a kyphotic curvature. Facet joints are located at the posterior side of the vertebral column, pairwise between the individual vertebrae and project upwards as extensions of the bone and link two adjacent vertebra together. The facet joints contribute to stabilizing the vertebral column and permit flexion and extension but limit side bending.(Marcus (2004))

Between most of the vertebrae are located fibrocartilaginous plates called intervertebral discs. These structures function as a shock-absorbing system, which protects the different structures in the vertebral column. The intervertebral discs play a moderate role in vertebral movement, but contribute in permitting extension of the upper body.(Marcus (2004)) Figure A.5 illustrates how the vertebrae are connected through facet joints and intervertebral discs.

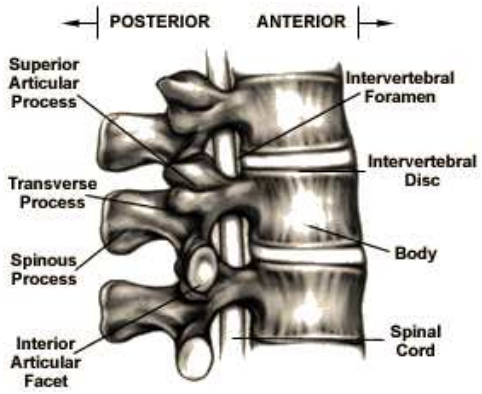

Figure A.5: Part of the vertebral column. The vertebrae are connected through facet joints and intervertebral discs. Illustration from `http://www.espine.com/Secondary-anatomy/spine-2.gif`

A.4 Posture-maintaining muscles and ligaments

The S-shape of the vertebral column minimizes the muscular activity required to maintain balance in a standing position (Martini (2004)). Several muscle groups are involved in movement and stability of the spine.

The anterior, prevertebral musculature lies close to the spine and therefore requires the assistance of other muscles to perform flexion movements (Marcus (2004)). The abdominal and iliopsoas muscle groups function as major flexors of the lumbar spine, aided by the oblique muscles.

The back extensor muscle group consists of the posterior muscles affecting the spine, including the erector spinae and the multifidus muscles.

Figure A.6 illustrates the largest posterior muscle groups; the erector spinae and the multifidus, and the anterior abdominal and oblique muscles.

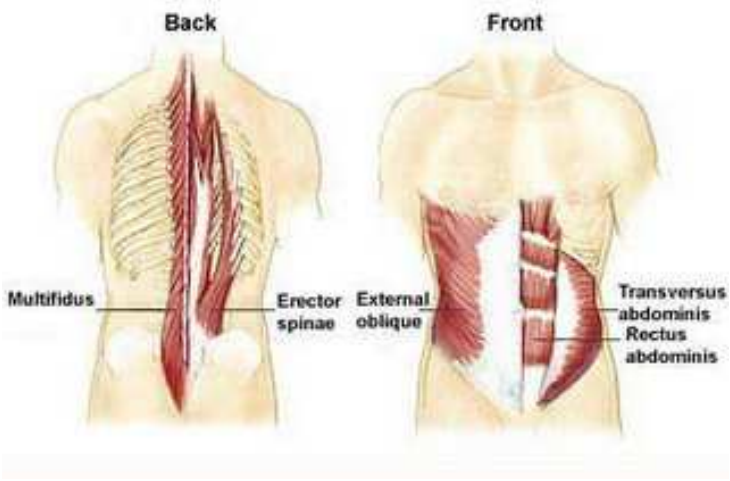

Figure A.6: The major anterior (flexor) and posterior (extensor) muscle groups. Illustration from `http://4.bp.blogspot.com/_Kggy_hfPwf4/R57KEIOj_gI/AAAAAAAAADk/pOE5rQwQRt4/s320/core+muscles2.jpg`

Figure A.7 illustrates the organization of the iliopsoas muscle group into psoas major, psoas minor and iliacus.

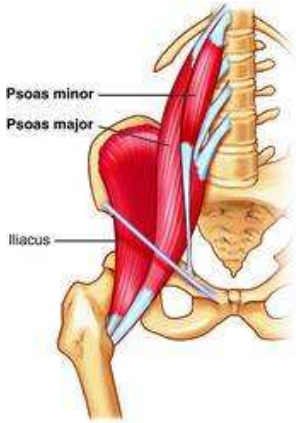

Figure A.7: The organization of the iliopsoas muscle group into psoas major, psoas minor and iliacus. Illustration from `http://img.tfd.com/MosbyMD/thumb/psoas_major_and_min.jpg`

The gluteal muscles make up the buttocks and are described in section A.1 and illustrated in figure A.1

The hamstring muscle group consists of the biceps femoris, semimembranosus and semitendinosus. They originate on the pelvic surface inferior and posterior to the acetabulum. Con-

traction of the hamstrings produce extension at the hip, as well as flexion of the knee.(Martini (2004)) Figure A.8 illustrates the organization of the hamstring muscles.

Figure A.8: The hamstring muscle group, consisting of the biceps femoris, semimembranosus and semitendinosus. Illustration from `http://www.andrewho.com.au/images/hamstrings.jpg`

Movement of the spine is constrained by tissue connecting the vertebrae (Hansen et al. (2006)). Ligaments are fibrous bands of tissue connecting two are more structures together, providing stability and limiting certain movements or preventing movement in certain directions.(Martini (2004))

The anterior and posterior longitudinal ligaments provide stability and provide protection for the disc and chords by linking the vertebrae together. The posterior arch ligaments provide stability and provide elastic energy during movement. They consist of several groups of ligaments that connect different parts of the vertebrae, providing counterforces and separating lamina during movements.(Marcus (2004))

The sacrum, the ilium and the lumbar spine are connected by the lumbo-pelvic ligaments, stabilizing all lumbo-pelvic movement Marcus (2004).

Appendix B

Subjective discomfort measurements

Discomfort is associated with pain, tiredness, soreness and numbness and can be mediated by factors such as joint angles, tissue pressure, muscle contractions and blood circulation (Helander and Lijian (1997)). In the field of ergonomics, ratings of discomfort are frequently used in the evaluation of seated posture. The perception of discomfort is individual and is influenced by anthropometric features, such as gender (Dunk and Callaghan (2005)).
The two most frequently used methods of recording subjective discomfort are the Visual Analogue Scale (VAS) (Cline et al. (1992)) and the Body Part Discomfort (BPD) scale (Corlett and Bishop (1976)). In the present study, it was found relevant to distinguish between discomfort in different body parts, as it was important to be able to verify that the observed discomfort arose due to the act of sitting. As such, the BPD scale was the obvious choice for the rating of seated discomfort in the present study.

B.1 Body Part Discomfort Scale

The BPD method, as the name indicates, assesses subjective discomfort in different body parts (Corlett and Bishop (1976)). The subject is asked to rate the level of discomfort in different body parts, starting with the body part with the most discomfort. The second most uncomfortable body part is then rated, and so on. In the present study, the BPD results were used to calculate the BPD index which is the sum of the ratings of all body parts (Helander and Lijian (1997)). In the present project, subjects are presented with an illustration of the human body segmented into nine parts (see figure B.1) to aid the subject in rating the discomfort in specific areas. The illustration is modified from Corlett and Bishop (1976), adding the popliteal area as a separate

body part to be able to evaluate the effect of the padding of the anterior edge of the force platform used as a seat pan.

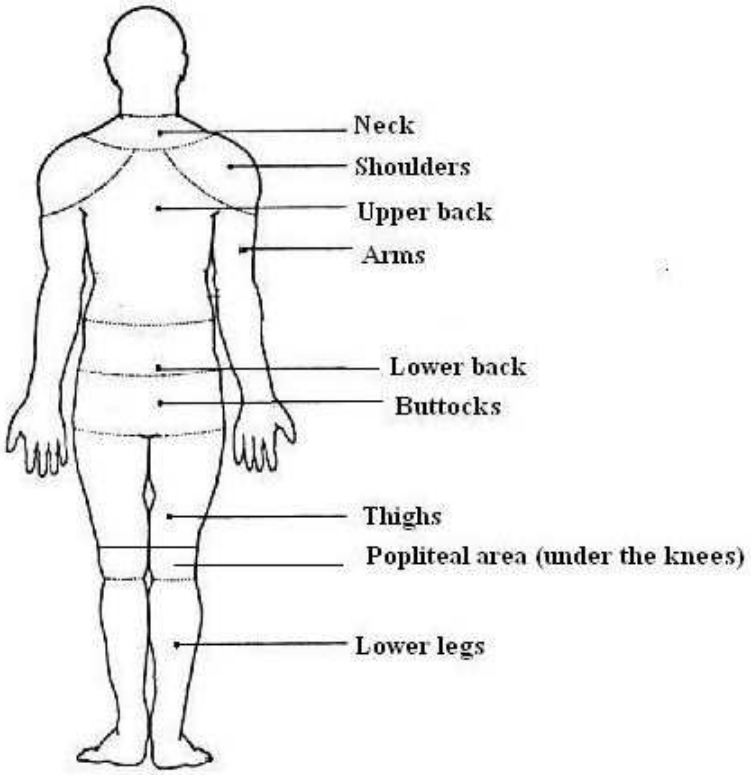

Figure B.1: Illustration of the human body, divided into nine body parts. The illustration is modified from Corlett and Bishop (1976)

The scores for each body part were manually written in a scheme by the examiners.

Appendix C

Motion capture

Kinematic measurements are performed using the Qualisys Proreflex 240 Camera System (Qualisys, Gothenburg, Sweden) and processed using Qualisys Track Manager (QTM) software. The system tracks the movement of the body through continuous infrared recording of reflective markers attached to an object (in the present study anatomical landmarks refering to lumbar curvature). A minimum of two cameras is needed to generate 3D data from the 2D frames of each camera and the spatial information provided by calibrating the system before recordings. However, if using only two cameras, frames in which one or both cameras can not see the marker (e.g. if a hand or the like passes between the camera and the marker), no 3D data can be generated. As such, more cameras are commonly added to the setup, minimizing the risk of not being able to generate 3D data. In the setup of the present study, eight cameras were used, spaced evenly around the subject, as illustrated in figure C.1. The green dots show the reflective markers on the body of the subject.

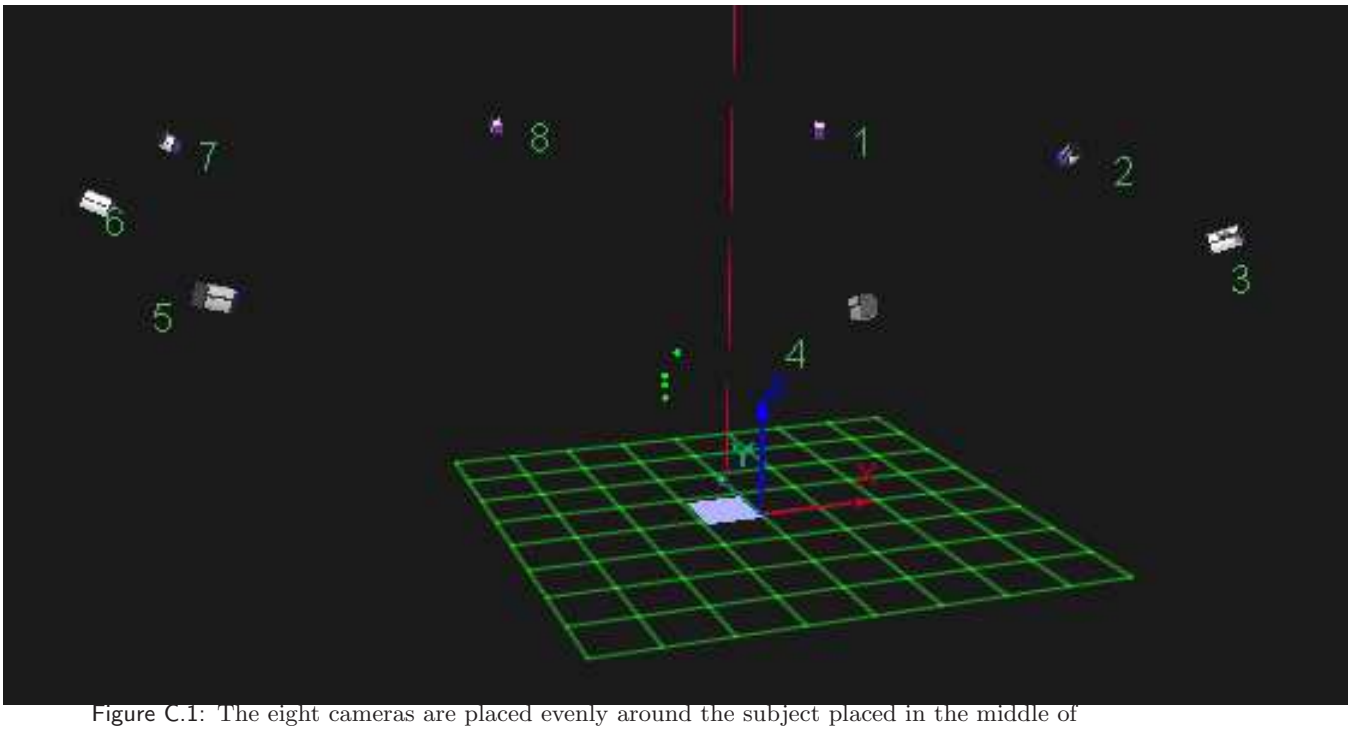

Figure C.1: The eight cameras are placed evenly around the subject placed in the middle of the room. The green dots show the reflective markers on the body of the subject.

Once a marker has been identified, it is tracked throughout the recording, and its trajectory can subseqently be analyzed. 3D positions of the markers were exported as tab separated (tsv) files and analyzed in MATLAB (Mathworks, Natick, MA).

Appendix D

Calculation of center of pressure

Center of pressure (COP) is the point of contact at the supporting surface through which the ground reaction forces are considered to act. In the present study, COP was calculated from kinetic data recorded through a force platform functioning as a seat pan. Figure D.1 illustrates a force platform, which measures the three orthogonal force components along the X, Y and Z axes ($F_x,\ F_y$ and F_z) and the moments around each axis ($M_x,\ M_y$ and M_z).

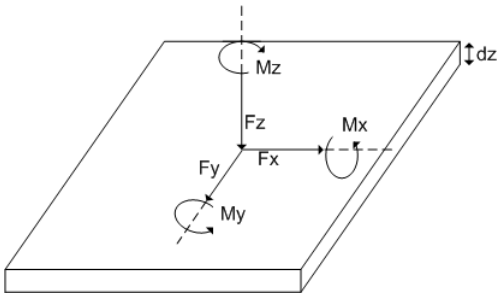

Figure D.1: Force platform measuring the three orthogonal force components along the X, Y and Z axes and the moment around each axis. dz is the thickness of the plate.

The force platform used in this experiment was an AMTI OR6-7 1000 platform with serial number 4009. The origin of the coordinate system differs from the geometric center of the top plate by $1mm$ along the negative X-axis, $0.28mm$ along the Y-axis and $39mm$ along the Z-axis. Calibration values differ for each individual platform. For the platform used in the present study, data are calibrated according to table D.1.

	Fx'	Fy'	Fz'	Mx'	My'	Mz'
Fx	1.522	-0.006	0.005	-0.007	-0.000	-0.002
Fy	0.007	1.1521	-0.007	-0.001	0.000	0.004
Fz	0.012	0.005	5.944	0.022	0.001	0.005
Mx	-0.000	-0.001	0.000	0.608	0.001	-0.001
My	-0.001	0.000	-0.000	0.002	0.610	0.001
Mz	-0.001	0.001	-0.001	-0.003	0.000	0.305

Table D.1: Calibration matrix

Each moment is composed of a couple and two moments of force so that

$$M_z = -F_x \cdot Y + F_y \cdot X + T_z \tag{D.1}$$

$$M_x = F_z \cdot Y + F_y \cdot d_z + T_x \tag{D.2}$$

$$M_y = -F_z \cdot X - F_x \cdot d_z + T_y \tag{D.3}$$

- F_x, F_y and F_z are the forces in the X, Y and Z direction, respectively
- M_x, M_y and M_z are the moments around the X, Y and Z axes, respectively
- T_x, T_y and T_z denote the couple around the X, Y and Z axes, respectively
- dz is the thickness of the plate $(41,3mm)$
- X and Y are the coordinates of the COP

As Tx and Ty can not occur in the experimental setup of this project, the coordinates for the center of pressure can be calculated from these quantities as follows:

$$X = \frac{-(M_y + F_x \cdot d_z)}{F_z} \tag{D.4}$$

$$Y = \frac{M_x - F_y \cdot d_z}{F_z} \tag{D.5}$$

Appendix E

Assessment of lumbar curvature

Various techniques for measuring lumbar curvature and pelvic tilt have been used throughout the literature. However, most require either the use of radiography (Lord et al. (1997)) or some type of specially designed equipment (Moes (1998)), which were not available when performing the present study. The settings available for the present project called for a measurement technique that could be performed non-invasively and without the use of specialized equipment. A widely used approach for measuring lumbar curvature is the Cobb method, which utilizes radiographic images and defines the angle of curvature based on the tilt of singular vertebrae. Chernukha et al. (1998) developed a technique similar to that of Cobb, but using points on the vertebrae and lines between them to define the angle. This method was the inspirational basis of the method developed for the present study.

E.1 TRALL measurement technique

Tangential radiologic assessment of lumbar lordosis (TRALL) was developed by Chernukha et al. (1998). It involves the use of radiographic imaging and estimates the angle of curvature as depicted in figure E.1.

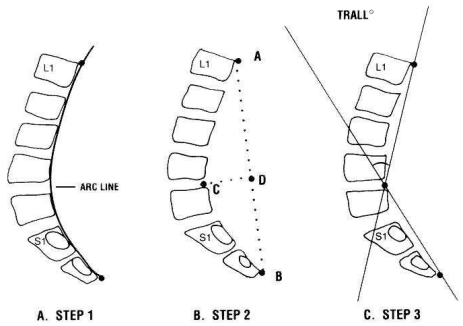

Figure E.1: A: a line is drawn along the curvature, B: a straight line is drawn between the posterosuperior margin of L1 and posteroinferior margin of S2, and a perpendicular line in drawn from that line and to the farthest point of the curvature line, C: a line is drawn between L1 and the point where the perpendicular line intersects the curvature and another between S2 and that same point. The angle is determined at the intersection between these two lines.(Chernukha et al. (1998))

The TRALL technique has been proven to be more reliable than the Cobb technique (Chernukha et al. (1998)), which is otherwise widely used for assessing lumbar curvature.

E.2 Modification to non-invasive measurement

As mentioned, the settings available for the present project call for the use of non-invasive measurements without the use of radiographic imaging. Thus, a new method was developed for assessing lumbar curvature, inspired by the TRALL method.
The landmarks used in the TRALL method are the posterosuperior margin of the L1 vertebra and the posteroinferior margin of the S2 vertebra. These landmarks are not directly palpable, but the spinous processes of the L1 and S2 vertebra can be identified non-invasively. This was utilized to modify the TRALL technique for the present project. Figure E.2 shows a schematic of the analogous, non-invasive measurement technique.

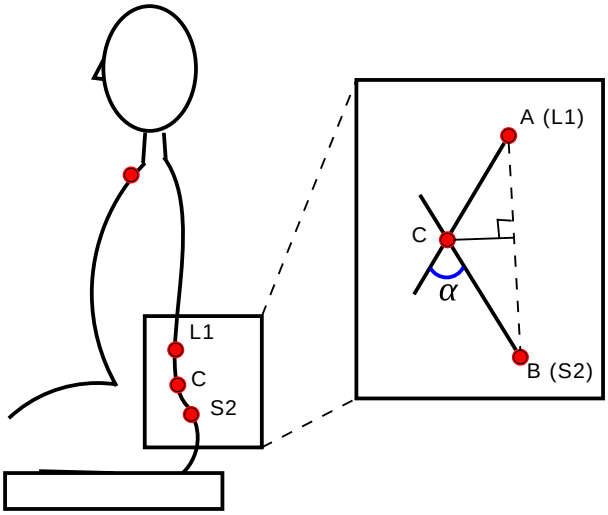

Figure E.2: Non-invasive measurement technique analogous to the TRALL method. Reflective markers were placed at the spinous processes of L1 (point A) and S2 (point B). At the farthest perpendicular distance between a line between these two markers and the lumbar arch, a third marker is placed (point C). α denotes the angle of lumbar curvature. A fourth marker was placed at the sternum as a reference point to discern lordotic and kyphotic postures computationally.

For each subject, the spinous processes of the L1 and S2 vertebrae were palpated and each marked with a reflective marker. During relaxed standing, the point on the lumbar spine with the furthest perpendicular distance to an imaginary line between point A at L1 and point B at S2, corresponding to point C in figure E.2, was found by sliding a ruler along the lumbar spine between A and B. The point C was also marked with a reflective marker.

The curvature was calculated for each sample as follows, with the upper, lower and middle back markers representing points A, B and C in figure E.2, respectively. The angle α was calculated as 180° minus the angle at C in the triangle ABC. The location of the sternum marker was used to determine whether the calculated angle was lordotic or kyphotic. The vectors (with the coordinates of the lower back marker representing origo, as in figure E.3a) determined by the markers were aligned with the yz-plane (figure E.3b) and rotated so that the line between the lower and upper marker was coincident with the z-axis (figure E.3c). This enabled discrimination based on the sign of the y-coordinates of the middle back and sternum markers. Lordotic curvature (i.e. the case where the sign of the sternum y coordinate was the same as that of the middle back marker y coordinate, figure E.3d) was counted as positive, while kyphotic curvature (i.e. the case where the sign of the sternum y coordinate was opposite that of the middle back marker y coordinate, figure E.3c) was counted as negative.

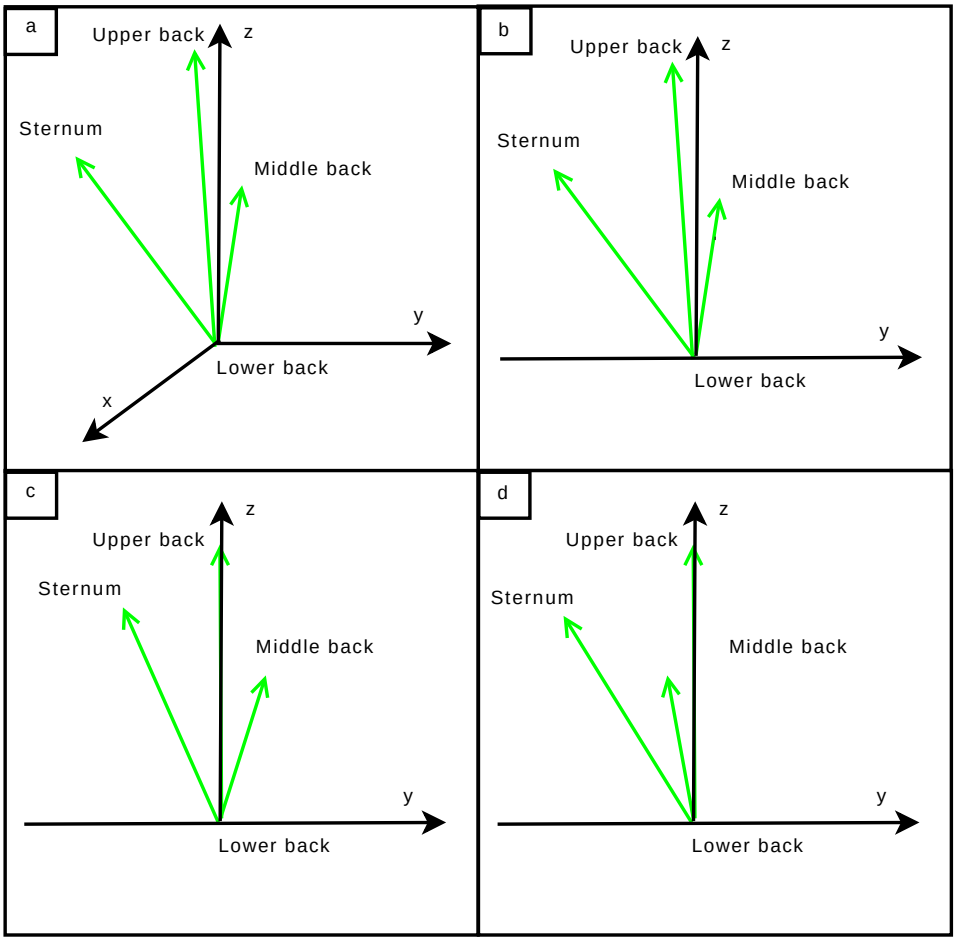

Figure E.3: Determining lordotic/kyphotic curvature. a) vectors defined by markers with origo at the coordinates of the lower back marker. b) Alignment of vectors with yz-plane. c) rotating to align vector from lower to upper back marker with z-axis (kyphotic curvature). d) lordotic curvature.

E.3 Palpation

Under guidance of Ph.d. student and former chiropractor, René Lindstrøm, a method was developed for the determination of the position of L1 and S2 easy to perform by non-clinical examiners as the authors of the present project. According to René Lindstrøm, the problems with external palpation of vertebrae are the frequent anatomical abnormalities seen in the population, that are typically not possible to determine without the use of radiographic imaging, i.e. extra, missing or somehow deform vertebrae. We acknowledged this limitation and made the assumption that our subjects have normal spines and proceed under this assumption.
The C7 vertebra is readily palpable, and when instructing the subject to assume a pronounced kyphotic thoracic posture, the thoracic vertebrae are, as well. The level of L1 is determined

from palpating C7 and counting down the 12 thoracic vertebrae to the first lumbar vertebra, L1. This procedure assumes 12 normal thoracic vertebrae and a normally shaped C7 vertebra. Figure E.4a illustrates the method.

The S2 vertebra is not easily palpatable, and another option was identified for identifying the S2. The fifth lumbar vertebra, L5, is palpatable, in that it is the last of the vertebra that is not rigidly attached to the sacrum. Therefore, manually bending the back of the subject backwards during palpation can reveal the transition between the lumbar and sacral parts of the vertebral column, and the location of S2 could be estimated as approximately 3 cm below this point. However, this procedure can be challenging and requires thorough experience with palpation of the vertebrae. Therefore, it was considered more likely to yield accurate results to estimate the position of S2 by measuring 7 cm (estimated based on a mean height of approximately 185 cm) down from the point on the spine intersected by an imaginary line between the left and right iliac crests. Figure E.4b illustrates this method.

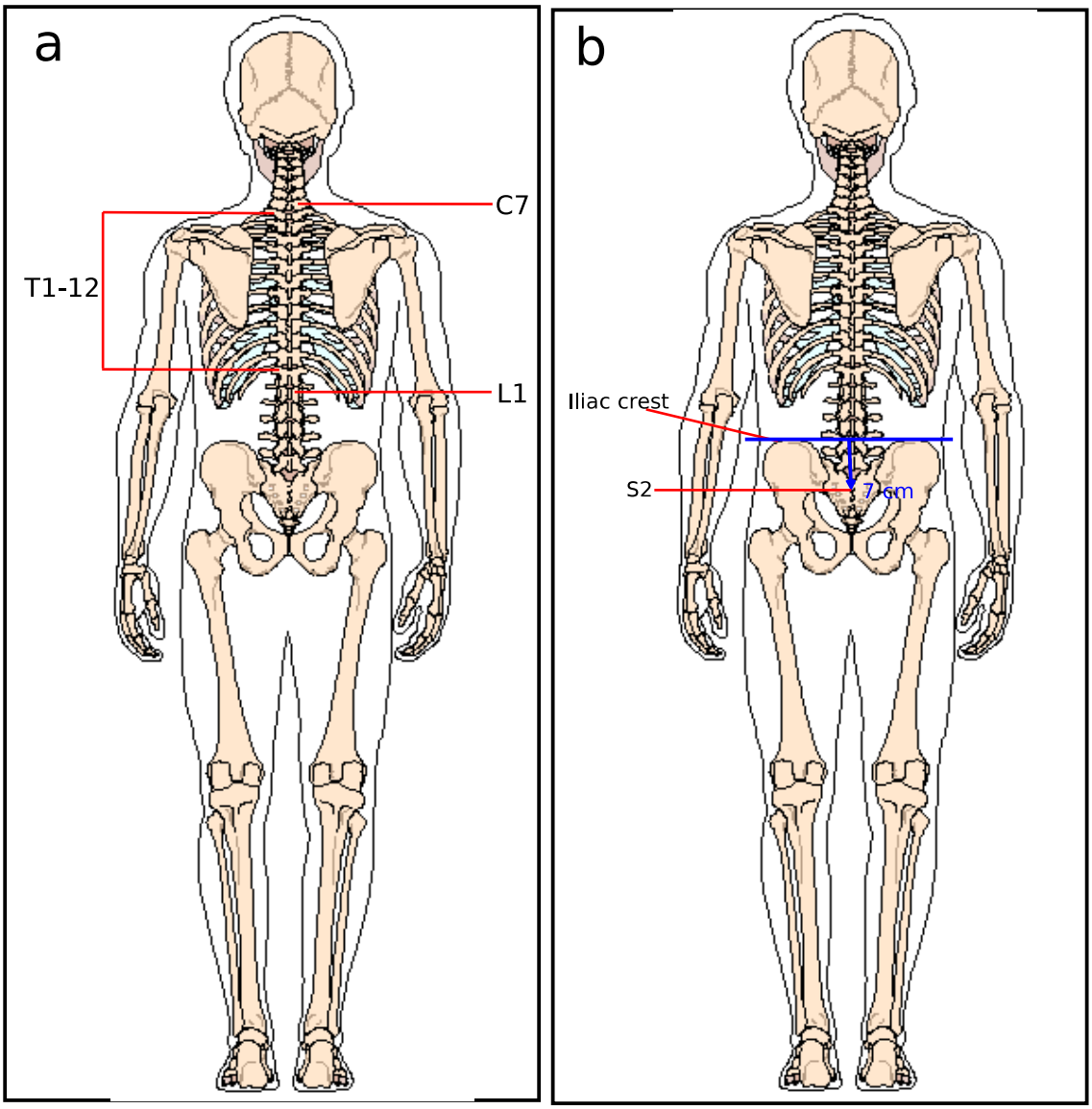

Figure E.4: Palpation of the spinous processes of the L1 and S2 vertebrae. a: L1 is located by palpating C7 and counting down the 12 thoracic vertebrae. b: S2 is located by measuring 7 cm down the spine from the level of the iliac crest. Figure is modified from `http://shs.westport.k12.ct.us/mjvl/anatomy/skeletal/whole_skeleton_with_body_outline.gif`

E.4 Limitations

Compared to the use of radiographic measurements for determining lumbar curvature, the manual placement of markers will introduce a source of error in the measurement. The vertebrae depicted in figure E.1 only illustrate the vertebral bodies, and refrains from illustrating the spinous processes, which are the parts of the vertebrae that are actually externally palpable.

When using the original TRALL method, the points of reference on the lumbar spine are at the superior posterior end of each vertebrae, which is different from the landmarks that are palpated in the method used in the present project. This poses a limitation in that we will not be able to directly compare our results with other studies using the TRALL method. To minimize the influence of the source of error that comes from the manual marker placement, one experimenter will perform the placement for all subjects, after having practiced thoroughly the palpation of the anatomical landmarks.

E.5 In-chair movement frequency

The frequency of postural changes has been shown to be correlated with seated discomfort (Vergara and Page (2002);Fenety et al. (2000)), and provides a measure of the amount of variability of seated posture. Low pass filtering center of pressure or kinematic data provides a method for assessing global postural changes, also referred to as in-chair macromovements. In-chair macromovements are counted based on threshold counting (Vergara and Page (2002)). High pass filtering the same data yields an expression of small movements around postures, also referred to as in-chair micromovements (Fenety et al. (2000)), and are typically counted as zero-crossings (Vergara and Page (2002)).
Based on the discussion presented in the introduction, regarding the inconsistent recommendations regarding which lumbar curvature fascilitates the most optimal seated posture, we were interested in large global postural changes in lumbar curvature, more specifically shifts between lordotic and kyphotic lumbar postures. We therefore estimated the in-chair macromovement frequency of lumbar curvature, by low pass filtering the lumbar curvature time series and defining an in-chair movement as a zero-crossing of the filtered time series. The cut off frequency was chosen based on previous studies (Vergara and Page (2002)) as 1/20 Hz. The filter was designed as a second order Butterworth low pass filter.

Appendix F

Non-linear analysis

Non-linear time series analysis methods render possible a more comprehensive understanding of the dynamics of biological systems, which are complex of nature in that they are composed by an amount of feedback loops determining the response of the system to changes in the internal and external environments (Seely and Macklem (2004)). Data sets with the same linear statistics (such as mean, variance and standard deviation) may still exhibit different characteristics in terms of non-linear dynamics, which are not detected by use of linear analyses. Non-linear analysis methods supplement these basic statistical linear analyses in distinguishing between time series of different characteristics.(Seely and Macklem (2004))

F.1 Entropy measures

Entropy measures are part of the family of non-linear analysis techniques. They measure randomness and indicate the regularity of a system. Higher entropy means higher randomness and thus less regularity. Entropy is also interpreted as the rate of information generation and, as such, can be used to provide an estimate of the complexity of the underlying system producing the dynamics in question (Lipsitz and Goldberger (1992)). Practically, the regularity is assessed by detecting similarities of runs of predefined length, thus detecting repeating patterns in the data. In the present project, we employed sample entropy (SaEn), which was developed based on approximate entropy (ApEn).

F.1.1 Approximate entropy

The method for calculating ApEn was developed by Pincus et al. (1991) as a modification of the Kolmogorov-Sinai (K-S) entropy. The K-S entropy formulas are intended for calculating regularity of noiseless data from deterministic systems and thus are very sensitive to noise. Also, the amount of data required to compute the K-S entropy increases exponentially with the dimensionality of the system. Hence, in order to be able to determine a measure of entropy for clinical data, for which the underlying system can not be expected to have a low dimensionality, a vast amount of data is required. Also, some noise is essentially always present in clinical data. Thus, a measure was required, that was less sensitive to noise, and that required a smaller amount of data for providing a valid estimate of the entropy of biological systems. ApEn was developed to overcome these limitations of K-S entropy for clinical applications.(Pincus et al. (1991))
To calculate the entropy of a time series of length N, initially, a series of vectors, $x(i),\ 1 < i < N - m + 1$ are formed from the original data, $u(i),\ 1 < i < N$, with

$$x(i) = [u(i), u(i + L), u(i + 2L)..., u(i + (m - 1)L)] \tag{F.1}$$

(Pincus et al. (1991))
Each vector $x(i)$ now forms a subset of the original data set to be compared with other subsets. m denotes the length of each vector (embedding dimension) and thereby determines the size of the patterns for which repetitions are evaluated, and L denotes the lag.(Pincus et al. (1991))
Next, the similarity of these vectors is evaluated by defining the distance between two vectors, $x(i)$ and $x(j)$ by the maximum difference in their respective scalar components, i.e.

$$dist[x(i), x(j)] = max[|u(i + k) - u(j + k)|], \quad 0 \geq k \geq m - 1 \tag{F.2}$$

(Richman and Moorman (2000))
$x(i)$ being the *template*. Every comparison that yields a distance lower than, or equal to, some specified value, r, is counted, termed a *template match*. The value of r thus represents a filtering level and must be chosen carefully. To overcome the problem with the influence of noise, when computing ApEn, data comparisons are made on a scale larger than most the noise. Practically, this is done by defining r in terms of the standard deviation (SD) of the data series. Too low an r-value will cause very few comparisons meeting the requirement and thus will yield an artificially high entropy measure, whereas too high a value will cause loss of detailed system information, and result in an artificially low entropy measure. Values of r are recommended to lie between 0.1 and 0.25 times the SD of the data set.(Pincus et al. (1991))
The next step of calculating ApEn is to determine the probability that a match occurs, for each

increment of i, i.e.

$$C_i^m = \frac{number\ of\ x(j)\ such\ that\ d[x(i), x(j) \leq r]}{N - m + 1} \tag{F.3}$$

(Pincus et al. (1991))
and for the entire sequence, averaging over i, i.e.

$$\Phi^m(r) = \frac{\sum_{i=1}^{N-m+1}(ln\ C_i^m(r))}{N - m + 1} \tag{F.4}$$

(Pincus et al. (1991))
Fixing m and r is what separates ApEn from K-S entropy, which is only defined for m and r approaching infinity, allowing ApEn to be calculated as an actual algorithm as opposed to the abstract formulas of K-S entropy.(Pincus et al. (1991))
ApEn is a measure of the probability that if runs of patterns are close, they will remain close on next incremental comparisons, i.e.

$$ApEn = \Phi^m(r) - \Phi^{m+1}(r) \tag{F.5}$$

(Pincus et al. (1991))
It must be noted that ApEn(m,r) is a *family* of formulas and ApEn(m,r,N) is a *family* of statistics estimating ApEn(m,r), and that different choices of m and r will yield different results, even for the same system (Pincus (1991a)). However, ApEn is not intended to provide an absolute value, rather, it is intended as a tool to compare systems. Caution must be made when trying to compare ApEn measures for different systems.(Pincus et al. (1991))
Time series with the same linear characteristics can have different entropy measures, just as evenly regular time series can have different linear characteristics. Therefore, it is essential to use ApEn in conjunction with moment statistics in order to provide a more complete picture of the properties of the data set and the underlying mechanisms.(Pincus et al. (1991))

Though providing new possibilities for evaluating entropy of clinical data series, ApEn has an inherent bias, in that the algorithm counts self-matches in equation F.3 to ensure at least one match within r for each template and thereby avoid the occurence of $ln(0)$ in equation F.4. This bias results in a lower value of ApEn for shorter records than expected, making it sensitive to sample length, i.e. the larger N, the less influence the bias will have.
To illustrate the influence of the bias of ApEn, equation F.5 is rewritten as follows

$$ApEn = \Phi^m(r) - \Phi^{m+1}(r) \tag{F.6}$$

⇕

$$ApEn = \frac{\sum_{i=1}^{N-m+1}(ln\ C_i^m(r))}{N-m+1} - \frac{\sum_{i=1}^{N-m}(ln\ C_i^{m+1}(r))}{N-m} \tag{F.7}$$

⇕

$$ApEn = \frac{\sum_{i=1}^{N-m+1} ln\ (\frac{B_i}{(N-m+1)})}{N-m+1} - \frac{\sum_{i=1}^{N-m} ln\ (\frac{A_i}{N-m})}{N-m} \tag{F.8}$$

(Richman and Moorman (2000))
- where B_i denotes the number of $x_m(j)$ within r of $x_m(i)$ and A_i denotes the number of $x_{m+1}(j)$ within r of $x_{m+1}(i)$. For large N:

$$ApEn \approx \frac{\sum_{i=1}^{N-m}(-ln\frac{A_i}{B_i})}{N-m} \tag{F.9}$$

(Richman and Moorman (2000))
-with A_i/B_i being the conditional probability of a match, given a match in the previous incremental step. As discussed earlier, this formula holds the risk of having to deal with ln(0) if no matches occur. To overcome this, ApEn introduces a bias in that $A_i = A_i + 1$ and $B_i = B_i + 1$, where the conditional probability will always be higher than the true conditional probability A_i/B_i. Inconsistency of ApEn (in that pairs of parameters m and r do not produce the same relative ApEn value as other pairs) is also due to this bias, in that increasing r will increase the number of template matches, making the bias less influential and vice versa.(Richman and Moorman (2000))

The largest effect of this bias is seen when $A_i = B_i = 0$, meaning that there are no matches and the data in question is not regular at all. In this case, the probability of the template will be calculated as $(A_i + 1)/(B_i + 1) = (0 + 1)/(0 + 1) = 1$, indicating high regularity when actually, none is present.
Also, ApEn has proven inconsistent in some cases.(Richman and Moorman (2000))

F.1.2 Sample entropy

With the above motivation, Richman and Moorman (2000) developed the measure of sample entropy (SaEn). The algorithm of SaEn is similar to that of ApEn, although self-matches are not counted, making it less sensitive to sample length, N. Also, the algorithm itself has been reduced by approximately 50% in computation time relative to the computation time of

ApEn.(Richman and Moorman (2000))
SaEn does not count selfmatches and therefore is free of the bias just described. Intuitively, discarding selfmatches would lead back to the problem of the possible occurrence of $ln(0)$ in the calculations if any template $x(i)$ does not find a match. For SaEn, the algorithm is changed so that as long as one template finds one match, SaEn is defined, despite not counting self-matches.(Richman and Moorman (2000)) SaEn is determined as follows:

$$B_i^m(r) = \frac{number\ of\ x_m(j)\ within\ r\ of\ x_m(i)}{N-m-1}\ ,\ 1 \geq j \geq N-m\ ,\ j \neq i \tag{F.10}$$

$$A_i^m(r) = \frac{number\ of\ x_{m+1}(j)\ within\ r\ of\ x_{m+1}(i)}{N-m-1}\ ,\ 1 \geq j \geq N-m\ ,\ j \neq i \tag{F.11}$$

$$B^m(r) = \frac{\sum_{i=1}^{N-m} Bmi}{N-m} \tag{F.12}$$

$$A^m(r) = \frac{\sum_{i=1}^{N-m} Ami}{N-m} \tag{F.13}$$

(Richman and Moorman (2000))
$B^m(r)$ is the probability that two sequences will match for m points, while $A^m(r)$ is the probability that two sequences will match for $m+1$ points. Then,

$$SaEN = ln\left(\frac{A^m(r)}{B^m(r)}\right) \tag{F.14}$$

(Richman and Moorman (2000))
By this definition, SaEn is calculated based on a probability associated with the whole time series, whereas ApEn is calculated in a template-wise fashion. This is what ensures that SaEn is defined as long as at least one match occurs throughout the entire data set, excluding the need for nonzero probabilities for each template, thereby overcoming the need for counting selfmatches and thus the bias of ApEn, at the same time making it less sensitive to outliers. Also, SaEn shows better consistency across pairs of m and r due to the fact that the self-match bias is eliminated.(Richman and Moorman (2000))

F.1.3 Parameters

Choice of parameters m (embedding dimension), L (lag) and r (filter level) is critical to obtain reliable measures of entropy. Several methods have been proposed to calculate the appropriate parameters to use in non-linear analyses, but the literature does not yet offer a clear answer to which method is best to determine the appropriate parameters, as it depends on the type of

data to be analysed. However, one method has proven successfull in estimating an appropriate embedding dimension and lag over a range of data types and noise levels, i.e. specifying the lag as the first minimum of the average mutual information function and subsequently specifying the embedding dimension using the global false nearest neighbor method (Cellucci et al. (2003)). Mutual information is a measure of the information shared by two random variables and quantifies the information gained about one variable by measuring the other, i.e. to which extent measuring one of the variables will reduce the uncertainty of the other. In turn, the calculated mutual information, based on the joint and separate probability density functions, provides an estimate of the dependency of the variables, where the mathemathical description yields a value of zero for completely independent variables. For a discrete time series x, the two random variables are chosen as

$$R_1 = \text{the value of } x \text{ at time } i \tag{F.15}$$

and

$$R_2 = \text{the value of } x \text{ at time } i + \tau \tag{F.16}$$

-τ being a time shift variable.(Cellucci et al. (2003))
By plotting the mutual information against τ and choosing the value of τ at the first minimum of the mutual information function as the lag, L, yields reasonable results.(Cellucci et al. (2003))

The global false nearest neighbor method can be used to determine an appropriate embedding dimension. False nearest neighbors are points that are close in $\Re\ m$ but not in $\Re\ m+1$ and occur if the embedding dimension is too small. Calculating the percentage of false nearest neighbors for values of m will yield the smallest value of m that does not produce any false nearest neighbors. This value of m is chosen as the embedding dimension.(Cellucci et al. (2003))

As stressed earlier, the importance of methodological similarity is great when comparing entropy measures across data sets. Therefore, rather than determining the parameters from the methods described above, they were chosen based on previous studies to promote consistency. An embedding dimension of 2 was chosen.
We choose not to implement a time lag, acknowledging that the data may be oversampled, but recognizing the purpose of the study to discern *changes* in entropy over time, which should not be affected by the possible influence of noise. Also, we again refer to the comparability of our results to previous studies and the importance of consistent parameter choices.
For an embedding dimension of 2, a filter level of $0.1 - 0.2 \cdot SD$ is said to produce a reasonable statistical validity of an entropy measure (Pincus (1991b)). We follow that recommendation in choosing r as $0.1 \cdot SD$ of each data set, as this should minimize the influence of noise on the calculated entropy. We choose a value of r in the lowest end of the recommended interval because of the experimental setup. We believe that the noise of that setup is by no means

larger than that of e.g. cardiovascular and heart beat recordings, which were to an extent the basis for the development of the ApEn and SaEn measures and therefore are believed to also form the basis of the recommended interval.

F.2 Surrogation

A basic assumption when performing non-linear analysis on time series data is that the underlying system is deterministic of nature with a non-linear structure, and that the observed variability is not only noise arising from the data collection process or from the system itself. A frequently used method for detection of non-linear structure in a time series is that of surrogation, developed by Theiler et al. (1992), in which surrogate data sets of the original time series are created and tested for significant differences in non-linear statistics with regards to those of the original data set.
Surrogate data sets are created by shuffling the contents of the original data. As such, the surrogate data represent random data, sharing certain characteristics (depending on randomization technique) with the original data. When doing so, one imposes a known underlying distribution to the surrogate data, i.e. some variant of stochastic distribution. As this relates to entropy measures; if the entropy of the shuffled (which would exhibit a large entropy value) and the original data is the same, the underlying system of the original data can not be ascribed a non-linear structure. However, if the difference in entropy between the two data sets is statistically significant, the underlying system of the original data may be assumed non-stochastic, i.e. it may be assumed that the data has a deterministic origin.
There are several ways of creating surrogate data, depending on which question needs to be answered about the underlying dynamics of the original data. The most frequently employed surrogation method in the context of COP variability is described below.

F.2.1 Time randomized surrogate data

Time randomization is the simplest method of surrogation and is achieved simply by reorganizing the order in which the data occur in the time series, without manipulating the data itself. As such, the amplitude characteristics of the data are left unaltered, whereas any temporal correlations are removed from the series. This method allows one to answer the question of whether the original data is in fact only uncorrelated gaussian noise, or whether there is some temporal correlation of the original data.

Determinism of the underlying mechanisms of COP variability has already been demonstrated by various researchers throughout the literature (Myklebust et al. (1995);Roerdink et al. (2006);Her-

mann (2005);Duarte and Sternad (2008);Doyle et al. (2004);Cavanaugh et al. (2007);Donker et al. (2007);Donker et al. (2008);Harbourne and Stergiou (2003);Schmit et al. (2006)). On this basis, the surrogation procedure is omitted in the present project.

Appendix G

Data distribution analysis

To determine the nature of the data, we examined the data for homoskedasticity and normality. A dataset is homoskedastic if the variance of the dependent variable is the same for all values of the independent variable. Conversely, if the variance of the dependent variable varies for different values of the independent variable, the dataset is considered heteroskedastic. Heteroskedasticity will weaken regression analyses, but homoskedasticity is not as crucial as normality of the data. Homoskedasticity can for example be determined visually by checking the data scatterplots or residual plots from linear regression.

Normality was tested for each interval. To determine whether the data followed a normal distribution, we employed Q-Q plots. Q-Q plots compare the data with a theoretical distribution (normal when testing for normality). If all the data points fall close to a vertical line representing this theoretical distribution, the data can be considered normally distributed.

Furthermore, each interval was tested for statistical normality using the Shapiro-Wilk test, to substantiate the visual interpretation of the Q-Q plots. The Shapiro-Wilk test tests the null-hypothesis that the data comes from the same distribution as a theoretical, normally distributed data set, using a 0.05 level of significance. Thus, if the p-value falls below 0.05, the null hypothesis is rejected, and the data can not be considered normally distributed. If the null hypothesis is not rejected, it can not be said that the data do not come from a normally distributed population, and can therefore be treated as normally distributed during further processing.

G.1 Homoskedasticity

For all data sets except discomfort, the scatterplots showed little, if any, indication of heteroskedasticity (see figures 3.1-3.3). The heteroskedasticity of the discomfort data is not surprising, as all subjects naturally experienced close to no discomfort during the first intervals, minimizing the variance during these intervals. The heteroskedasticity weakens the analysis and increases the possibility of type I errors, i.e. false positives.

G.2 Normality

For discomfort, the first four intervals were not normally distributed according to the Shapiro-Wilk test, substantiated by visual inspection of Q-Q plots for these intervals. As all subjects experienced close to no discomfort during the first intervals, the range of discomfort of these intervals was limited to only a very few discrete values, for which normal distribution is very unlikely. A similar pattern of non-normality was found for lumbar curvature standard deviation, i.e. intervals 1-4 did not follow a normal distribution. We assumed normal distribution of the discomfort and lumbar curvature standsrd deviation data based on the results for the remaining intervals, indicating that the underlying data was normally distributed.
For the remaining parameters, both the Q-Q plots and the Shapiro-Wilk test indicated normally distributed data for the majority of the intervals, but with no apparent pattern for the intervals for which the tests did not. Based on these results, we assumed normal distribution of all data sets.
Figure G.1 shows an example of a Q-Q plot for a dataset with normal distribution, substantiated by a p-value over 0.05 in the Shapiro-Wilk test.

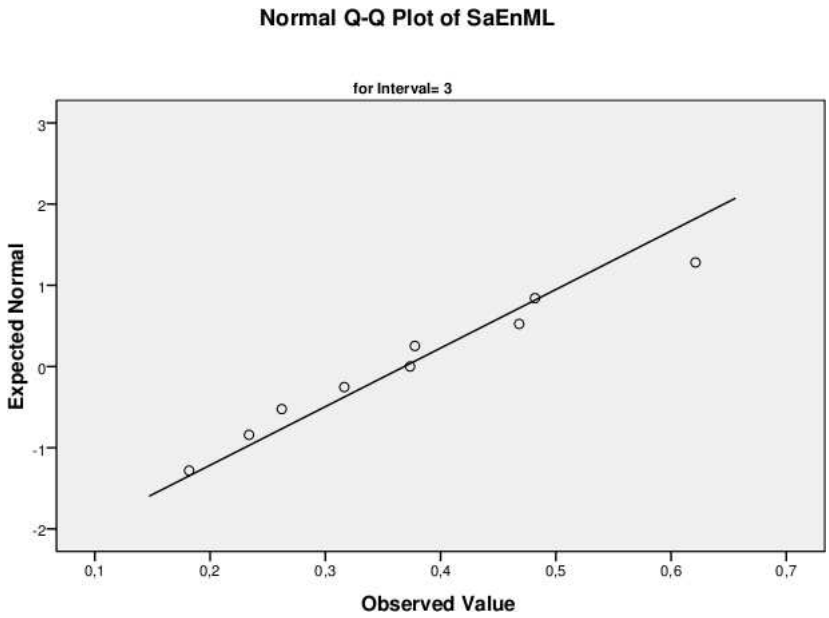

Figure G.1: Q-Q plot for medial-lateral sample entropy, interval 3. The plot indicates normally distributed data, as all the data points fall close to the vertical line representing a theoretical normal distribution.

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Variability and Complexity of Postural Control and Their Associations with Seated Discomfort.

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Abstract

The present study examined the variability of seated postural control during the development of seated discomfort by means of linear and non-linear analysis techniques. Nine male subjects participated in the study. Discomfort ratings, kinetic and kinematic data were sampled during prolonged sitting. Body Part Discomfort index, medial-lateral and anterior-posterior center of pressure components and lumbar curvature were calculated. For center of pressure components and lumbar curvature, mean posture, standard deviation and sample entropy were calculated, and in-chair movement frequency was calculated for the lumbar curvature. Correlation analysis was performed to determine the correlation of each parameter to discomfort. Results showed no correlations between discomfort and any of the mean posture variables. The amount of variability, in terms of standard deviation and in-chair movement frequency was positively correlated to discomfort for all variables, whereas complexity, in terms of sample entropy, decreased significantly during the development of discomfort for all variables. These findings suggest that objective postural parameters are interrelated with subjective discomfort, and that the importance of the dynamics of seated posture may challenge the idea of a static ideal seated posture.

Keywords: Complexity, sitting posture, postural control, discomfort, variability.

Introduction

Low back pain is one of the most costly disorders in the working population worldwide. It is the most common type of pain reported by adults (Sembrano and Polly (2009)), and has been shown by Volker (1991) to be related to lumbar curvature. Increased discomfort in the lumbar region has been found to be the main cause for increases in general discomfort in the seated position (Vergara and Page (2002)), and discomfort has been identified as a precursor to pain (Madeleine et al. (1998)).

Sitting has become the most common working-posture in today's society, where three-quarters of all workers in industrialised countries are associated with a workplace that requires prolonged sitting (Lis et al. (1975)) (e.g. video display units (VDU)). Such workstations have been associated with discomfort and infrequent postural changes (Fenety and Walker (2002)). Over the last years, there has been a shift in the understanding of the nature of sitting. Recently, it has been recognized as a dynamic rather than a static task, motivating research into the dynamics of seated postural control (Fenety et al. (2000)). Subjective discomfort and objective parameters, in terms of postural parameters and variability, are considered to be interrelated (Fenety and Walker (2002);Vergara and Page (2002)), and various studies have investigated the associations between different objective measures and discomfort to explore this phenomenon (Vergara and Page (2002);Liao and Druru (2000);Starr et al. (1985)), but results have so far been inconclusive. No studies have investigated the spatio-temporal characteristics of postural control signals in relation to subjective discomfort during prolonged sitting. The aim of the present study was to investigate the relations of subjective seated discomfort to the spatio-temporal, as well as the linear characteristics of postural control dynamics during the development of discomfort.

Linear analyses describe the constant relationships between two variables and can be used to quantify the variability of a time series. Liao and Druru (2000) used kinematic analysis

and subjective discomfort ratings to determine the associations between discomfort and the frequency of postural changes for subjects performing VDU work, and found a positive relationship. Substantiating these results, Fenety and Walker (2002) showed, by tracking center of pressure (COP) changes to detect in-chair movements, that the frequency of postural shifts increased over time during VDU work.

However, linear analysis does not provide a full overview of changes in postural control, as changes can occur in the patterns of the system outputs, which are not detected by linear analysis. Non-linear analysis is a family of mathematical measures that provides spatio-temporal characteristics of a time series (Seely and Macklem (2004)). To this time, non-linear analysis methods have been applied to time series from a broad range of biological systems, including the cardiovascular system, the central nervous system and the endocrinological system (Vaillancourt and Newell (2002)). In the field of biomechanics, non-linear analysis has often been applied to COP time series in the attempt to investigate the underlying dynamics of postural control. Entropy measures are part of the family of non-linear analysis techniques, and measure the randomness of a time series, and indicates the regularity of the system(s) producing the output. Higher entropy means higher randomness and thus less regularity. Entropy is also interpreted as the rate of information generation and, as such, can be used to provide an estimate of the complexity of the underlying system producing the dynamics in question (Lipsitz and Goldberger (1992)). In biological systems, various research has shown a relation between the degree of complexity and the state (healthy/ill) of the system (Vaillancourt and Newell (2002)), yielding measures of complexity highly relevant for clinical applications. For example, low back pain has been shown to be associated with a decrease in complexity of electromyographic activity of the lower back muscles (Sung et al. (2007)), and knee damage has been shown to be associated with a reduced complexity of the gait cycle (Georgoulis et al. (2006)).

The response of physiological systems to disease has been debated in the literature (Vaillan-

court and Newell (2002);Lipsitz and Goldberger (1992)), results indicating that the intrinsic dynamics of the system in question influences the direction of change in complexity. For systems with fixed point attractors, i.e. systems for which the output tends to return to the same value following perturbations, the complexity of the output tends to decrease due to pathology, whereas the opposite has been demonstrated to be the case for systems with oscillating intrinsic dynamics, i.e. systems for which the value that the output tends to return to after perturbations, varies over time (Vaillancourt and Newell (2002)).

Studies on standing postural control show a strong tendency of complexity of related physiological signals being negatively associated with disease (Vaillancourt and Newell (2002)). However, seated postural control has been only sparsely studied, despite the aforementioned vast significance of seated posture. In Hermann (2005) and Hermann and Bubb (2007), the relationship between seated COP dynamics and discomfort was investigated by simultaneously assessing driver macromovements as an indicator for discomfort and complexity of COP displacements during long term driving. As such, the study did not pertain to subjective discomfort, and it remains unanswered as to how variability measures of seated postural control relates to subjective discomfort.

In the present study, we evaluate seated dynamics as indicators of subjective seated discomfort during prolonged sitting, using both linear and non-linear analysis techniques. It is hypothesized that an increase in discomfort is related to an increase in the amount of variability, and a decrease in complexity of COP and of lumbar curvature displacement and a decrease in lumbar curvature.

Methods and materials

Subjects

Nine male volunteers participated in the study (mean±SD age 25.2±1.6 years, height 186.9±5.8 cm, weight 81.6±6.5 kg and BMI 23.3±1.1). None of the subjects had any known spinal deformities or history of back pain. All participants gave their informed consent to participate in the study. The study was approved by the local ethics committee (N-20070004MCH) and conducted in conformity with the Declaration of Helsinki. All subjects signed an informed consent.

Experimental procedure

The method for assessing lumbar curvature was modified from the TRALL (Tangential Radiologic Assessment of Lumbar Lordosis) technique (Chernukha et al. (1998)) to allow for non-invasive assessment of lumbar curvature (see figure 1 for a schematic illustration of the modified method). The spinous processes of the L1 and S2 vertebrae were palpated and each marked with a reflective marker. During relaxed standing, the point on the lumbar spine with the furthest perpendicular distance to an imaginary line between L1 and S2, corresponding to point C in figure 1, was found by sliding a ruler along the lumbar spine between L1 and S2 and marked with a reflective marker. A fourth marker was placed on the sternum as a reference for discerning kyphotic and lordotic lumbar curvatures. Subjects were seated on a force platform with no back-, foot- or armrest. As such, the only contact surface was the force platform. The subjects were allowed to move their upper bodies in response to discomfort, but were given restrictions with respect to movement of arms and feet, i.e. they were instructed to leave their hands at rest on their thighs, and not to move their legs and feet during recording. To avoid discomfort at the popliteal area from resting the thighs against the sharp edge of the force plat-

form, the edge of the force platform was padded. Each session consisted of 18 intervals of data recording with a break of 20 seconds between each interval, resulting in a total of 96 minutes for each session (as illustrated in figure 2). The breaks were inserted for discomfort assessment and to allow the subjects to move their lower legs and feet to ensure blood circulation in the legs. During the experiment, the subjects watched a movie.

Data recording

Every 5 minutes, during the 20 second break, Body Part Discomfort (BPD) ratings were collected according to Corlett and Bishop (1976), using a 6 level scale from 0 to 5, 0 representing "no discomfort" and 5 representing "worst imaginable discomfort". Each subject was presented with an illustration of the human body segmented into 9 different body parts, and was asked to rate his level of discomfort in each region. Reaction forces and moments were sampled at a rate of 100 Hz from an AMTI OR6-7 1000 force platform with a gain of 4000 and hardware low pass filtered with a cut off frequency of 10.5 Hz. Kinematic data was sampled at a rate of 100 Hz by use of the Qualisys Proreflex 240 Camera System (Qualisys, Gothenburg, Sweden) with an eight camera setup.

Data analysis

BPD scores for each subject were summed for each interval, providing a BPD index (Helander and Lijian (1997)). Force platform data was transformed to COP coordinates using MATLAB (Mathworks, Natick, MA). Kinematic data was processed using Qualisys Track Manager (QTM) software and was exported to MATLAB and transformed to lumbar curvature angle. Negative values denoted kyphotic curvatures and positive values denoted lordotic curvatures. For each variable (i.e. medial-lateral and anterior-posterior COP components and lumbar curvature), mean and standard deviation were calculated using MATLAB.

Sample entropy was calculated for all parameters, using MATLAB. Entropy quantifies regularity in a data series by assessing the probability that sequences of length m that are similar will remain similar when incrementing the length of the sequences to $m+1$. The similarity condition is determined by the tolerance, r. Output is a unitless, non-negative number where higher values indicate more complex data series. For a detailed mathemathical derivation of the formulas, see Richman and Moorman (2000). The embedding dimension, m, was chosen as 2, and the tolerance, r, was chosen to 0.1 times the standard deviation of the data series, in accordance with the recommendations of Pincus (1991). Finally, the in-chair movement frequency (in terms of zerocrossings pr. second after 1/20 Hz second order Butterworth low pass filtering) was calculated for the lumbar curvature variations for each of the 18 intervals.

Statistical analysis

To associate changes in the dynamics of postural control to perceived discomfort, multiple linear regression analysis was employed, with BPD index as the dependent variable and mean of medial-lateral and anterior-posterior COP component and lumbar curvature, sample entropy of medial-lateral and anterior-posterior COP component and lumbar curvature, standard deviation of medial-lateral and anterior-posterior COP component and lumbar curvature, and lumbar curvature in-chair movement frequency as predictor variables. Statistical analysis was performed using SPSS version 16.0 (Chicago, IL, USA). $p<0.05$ was considered as significant. Mean$\pm$SD are presented.

Results

Of the nine body regions that constitute the body part discomfort index, the buttocks and the lower back accounted for app. 43% of the recorded discomfort. Figures 3, 4 and 5 illustrate the tendencies of the assessed parameters over time. Each color refers to a specific subject, and the red lines illustrate linear regression of the data sets. BPD increased significantly over time (figure 3). Mean of the anterior-posterior COP component (figure 4a) and mean lumbar curvature (figure 4c) increased significantly over time, while mean of the medial-lateral COP component (figure 4b) did not change significantly. Results showed an increase in the amount of variability for both anterior-posterior and medial-lateral COP components and lumbar curvature (figures 4d, e and f) and in-chair movement frequency (figure 5). All increases were statistically significant ($p<0.05$ with a confidence level of 0.05. Complexity decreased over time for all investigated variables, as expressed by a statistically significant ($p<0.05$) decrease in sample entropy (figure 4g, h and i).

Table 1 lists the results of the multiple regression. There were statistically significant correlations between BPD and all predictor variables besides mean lumbar curvature and mean of anterior-posterior and medial-lateral COP components. Standard deviation was positively correlated with BPD for all parameters. Also, in-chair movement frequency was positively correlated with BPD, substantiating the indication of increased amount of variability with increased discomfort. Sample entropy was negatively correlated with BPD for all parameters.

Discussion

In the present study, we investigated the correlations between perceived discomfort and seated postural control, by means of linear and non-linear analysis of center of pressure displacement and variations in lumbar curvature while measuring seated discomfort.

Methodological considerations

The method for measurement of lumbar curvature was modified from a technique for assessing lumbar curvature in radiographic images (Chernukha et al. (1998)). This left room for inaccuracies in terms of palpation of anatomical landmarks, which was sought minimized through consulting a chiropractor to acquire experience with palpating the landmarks through skilled supervision.

In previous studies on seated discomfort, experimental setups have typically been directed towards some specific application, e.g. discomfort during driving (Hermann (2005);Hermann and Bubb (2007)) or in relation to specific chair designs (Vergara and Page (2002);Volker (1991)) or work tasks (Starr et al. (1985)). The drawback of this approach is the difficulty to discern the factors interacting with the perception of discomfort, i.e. whether it is associated to the sitting task itself, or whether it is associated with e.g. the work task. Furthermore, the presence/absence of backrest and armrests, etc., complicates comparisons between studies. As such, we omitted the backrest, armrests and cushion, and padded the front edge of the force platform to minimize discomfort in the popliteal area, as discomfort in this region does not, as such, pertain to the act of sitting as it does to shortcomings of the experimental design due to the design of the platform.

The setup of the present study has less direct clinical relevance, as the seating arrangement is far from any real seating arrangement used in practice. However, to gain scientific certainty in our claims regarding the correlations between perceived discomfort and the variables under investigation, it was imperative to exclude all factors that might influence the perception of discomfort in incalculable ways, e.g. work tasks or the presence of a cushion or backrest.

Postural variability measures as indicators of seated discomfort

The present study presents the correlations of subjective seated discomfort to mean posture, amount of variability and complexity of center of pressure trajectories and lumbar curvature. The predominance of discomfort observed in the back and under the buttocks confirms that the variables under investigation are in fact probable as indicators of seated discomfort, as they pertain to these anatomical regions.

Regarding mean posture, the hypothesis of the present study suggested a decrease in lumbar curvature to be associated with an increase in discomfort. To test this hypothesis, the mean curvature of each of the 18 intervals was calculated (see figure 4(c)). This procedure was repeated for each center of pressure component (anterior-posterior and medial-lateral direction, see figures 4(a) and (b), respectively) to further explore the associations of discomfort with global postural changes. Neither anterior-posterior or medial-lateral mean center of pressure components, nor mean lumbar curvature, showed any correlations with discomfort. These results suggest that mean posture variables do not provide an objective way to assess discomfort development.

The hypothesis also suggested that the amount of variability of both lumbar curvature and center of pressure displacement is positively correlated with discomfort. As figures 4(d), (e) and (f) illustrate, the standard deviation of all three variables did indeed increase over time, and as expressed in table 1, all showed statistically significant positive correlations with discomfort. In-chair movement frequency indicates the number of changes between kyphotic and lordotic postures (i.e. an indication of macromovements), whereas the standard deviation of the lumbar curvature denotes the *size* of the lumbar movements. In-chair movement frequency likewise increased over time (see figure 5) and showed statistically significant positive correlations with discomfort. The increase in standard deviation of center of pressure components and of lumbar curvature and in in-chair movement frequency over time all illustrate an increase in the amount

of variability. Gross medial-lateral center of pressure displacements are interpreted as a means of pressure relief of the gluteal region, as the peak pressure is lifted from either side. The increase in standard deviation with increased discomfort probably indicates a progressively larger need for greater/more effective pressure relief of the soft tissue under the buttocks, indicating associations between prolonged tissue pressure under the buttocks and discomfort. Given the lumbar-pelvic anatomy, with the shape of the spine closely intertwining with the tilt of the pelvis, the anterior-posterior center of pressure displacements are related to the variations in lumbar curvature, which is substantiated by the positive correlation observed between standard deviation of the lumbar curvature and standard deviation of anterior-posterior center of pressure displacement. Gross displacements of the lumbar curvature are likewise interpreted as a means of pressure relief, as changes in lumbar curvature rotate the pelvis and thus shift the location of the ischial tuberosities under the buttocks. Also, it may provide muscle- and ligamentous tension relief of the lumbar, sacral and gluteal body regions.

Results showed a decrease in sample entropy over time for all three parameters, i.e. anterior-posterior and medial-lateral center of pressure components and lumbar curvature (see figures 4(g), (h) and (i), respectively), along with significant negative correlations of sample entropy to discomfort. Comparison with other studies on changes in complexity is complicated, as the direction of change is related to both the intrinsic dynamics of the system in question and the type of condition causing the change in dynamics (Vaillancourt and Newell (2002)). However, there is a tendency for the postural control system to exhibit decreased complexity in the presence of pain or disease (Sung et al. (2007);Vaillancourt and Newell (2002)). Our results suggest that the intrinsic dynamics of seated postural control correspond with those of standing postural control, which are generally perceived as fluctuating around an equilibrium point (Collins and De Luca (1993)). Collectively, these results suggest that seated postural control has a fixed point intrinsic dynamic, and that discomfort affects this type of dynamic in

similar ways as does pain and disease.

Optimal seated posture

When the body is in neutral position, minimal strain is on the vertebrae. Postures oriented outside the neutral position may lead to increased muscle activity, discomfort and/or pain in the related body parts (Corlett (2006)). When muscles in the back contract, pressure is applied to the intervertebral discs (Corlett (2006)). Dynamical muscle activity is beneficial, as the discs gain nutrients from the pressure applied to them. Conversely, static activity can be harmful to the structures of the spine, in that when pressure is applied to the vertebrae, the discs creep and assume a more convex form at the rim. The discs may rupture and/or produce more pressure to the nerves in the spinal column.(Corlett (2006)) As such, lumbar curvature has been frequently used to define the most optimal seated posture. The literature offers contradicting recommendations for optimal seated posture with regards to lumbar curvature. Sanders and Ernest (1992) proposed a seated posture similar to that of the upright posture to be most ideal, based on physiological aspects of sitting, as a kyphotic lumbar curvature results in increased disc pressure. Conversely, Claus et al. (2008) questioned a lordotic posture to be the "ideal" sitting posture, in that a kyphosed lumbar posture requires less muscle activity than lordotic postures. Vergara and Page (2002) stated the necessity of varying the posture, in that some postures may be helpful for short periods but harmful for long terms. Though it requires more muscle activity to maintain a lordotic curvature than to maintain kyphosis, which, for prolonged sitting, may induce muscle fatigue, maintaining kyphotic curvatures elevates the intervertebral disc pressure and may cause stress to the ligaments that are stretched in this posture (Corlett (2006)). The results of the present study may aid in explaining the contradicting results in the literature on the subject of optimal sitting posture. Focus is most often on specifying some specific curvature that is least harmful, when in fact, as our results suggest, it is not the *value*

of the lumbar curvature, but the *variation* in the lumbar curvature that is associated with discomfort. Our results also support the statement made by Vergara and Page (2002) that some postures are harmful if sustained for a long period, viewing the increased variability of lumbar curvature as a means to relieve discomfort, arguing that seated discomfort is a pre-stage to damage to the anatomical structures involved in sitting.

The correlations between discomfort and standard deviation of lumbar curvature and in-chair movement frequency substantiate this notion that the posture itself is not as good a predictor of discomfort as is *variation* of the seated posture. This is substantiated by the lack of correlation between discomfort and mean center of pressure components and of lumbar curvature, and also by the significant positive correlations of discomfort to the amount of variability and complexity of center of pressure components and of lumbar curvature.

In conclusion, the present study proposes associations between subjective seated discomfort and the amount and complexity of center of pressure and lumbar curvature variability. As discomfort increased, movement patterns became more regular, and larger and more frequent movements were observed, but no effect was observed for mean posture variables. Further research is needed into the physiological mechanisms involved in the observed decrease in complexity of the postural control system, to provide a more complete understanding of the dynamics of seated discomfort, which may have implications for the recommendations for ideal seated posture.

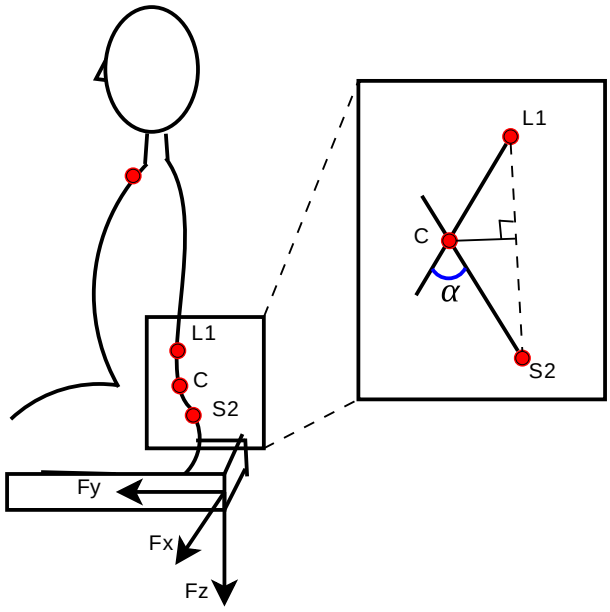

Figure 1: Experimental setup. Subject was seated on a force platform with no support for the back, feet or arms. The arrows in the coordinate system illustrated indicate the positive axes for the x, y and z force components. Reflective markers were placed at the spinous processes of L1 and S2. At the farthest perpendicular distance between a line between these two markers and the back, a third marker was placed. α denotes the angle of lumbar curveture. A fourth marker was placed at the sternum as a reference point to discern lordotic and kyphotic lumbar curvatures.

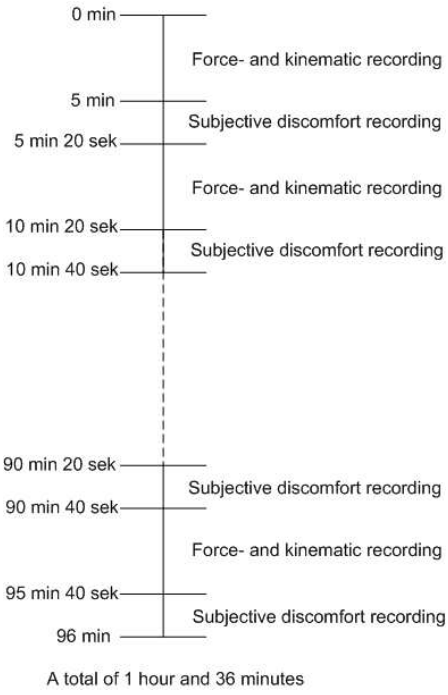

Figure 2: Time line for data recording.

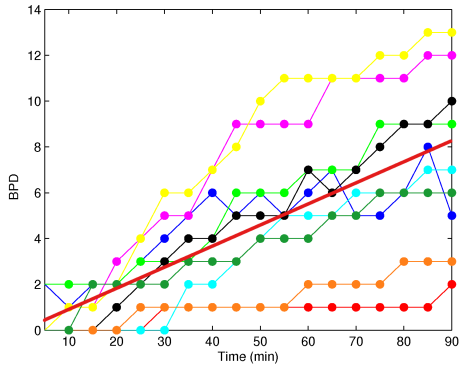

Figure 3: Body part discomfort index. Each color represents one specific subject. The red line illustrates the linear regression of each data set.

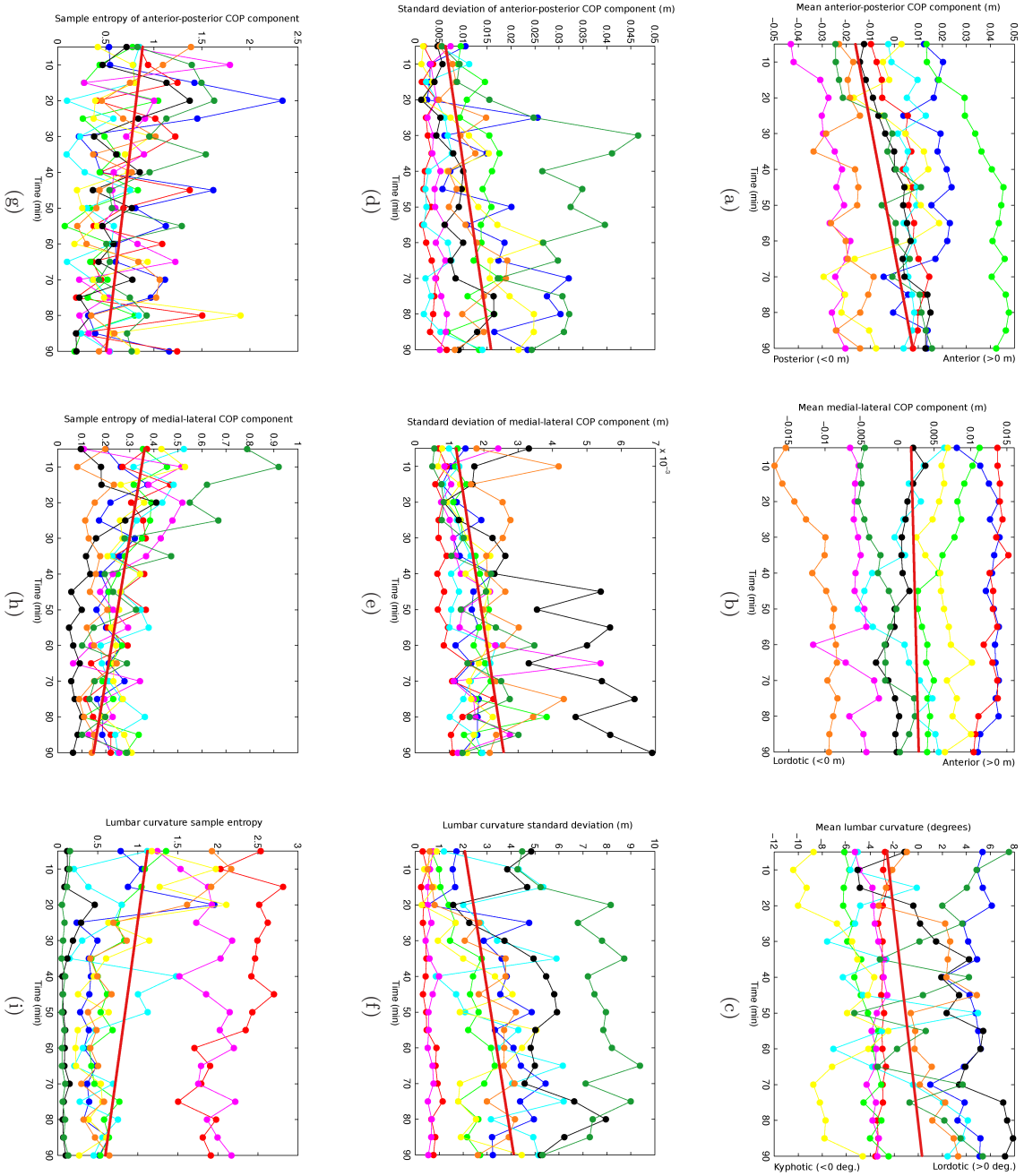

Figure 4: Mean (top row), standard deviation (middle row) and sample entropy (bottom row) of anterior-posterior (left column) and medial-lateral (middle column)) center of pressure components and lumbar curvature (right column). Each color represents one specific subject. The red lines illustrate the linear regression of each data set.

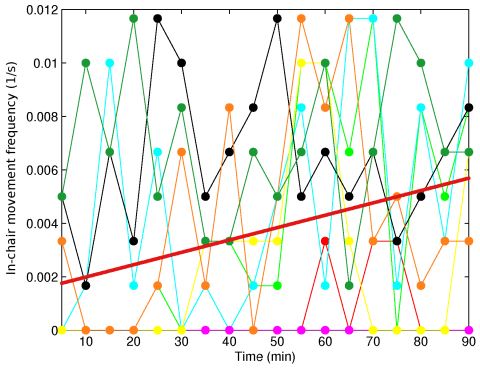

Figure 5: Lumbar curvature in-chair movement frequency. Each color represents one specific subject. The red line illustrates the linear regression of each data set.

Pearson											
	BPD	MLmean	APmean	LCmean	MLSaEn	APSaEn	MLSD	APSD	LCSD	LCSaEn	ICM
BPD	1	-	-	-	-	-	-	-	-	-	-
MLmean	0.029	1	-	-	-	-	-	-	-	-	-
APmean	0.125	0.541**	1	-	-	-	-	-	-	-	-
LCmean	-0.016	-0-091	0.065	1	-	-	-	-	-	-	-
MLSaEn	-0.278**	0.091	-0.120	-0.200**	1	-	-	-	-	-	-
APSaEn	-0.271**	-0.070	-0.235**	0.128	0.098	1	-	-	-	-	-
MLSD	0.329**	-0.313**	0.052	0.361**	-0.696**	-0.134*	1	-	-	-	-
APSD	0.273**	0.003	0.158*	0.171*	-0.151*	0.097	0.163*	1	-	-	-
LCSD	0.140*	-0.139*	0.139*	0.480**	-0.162*	-0.033	0.357**	0.675**	1	-	-
LCSaEn	-0.193**	0.113	-0.252**	-0.392**	0.166*	0.116	-0.368**	-0.565**	-0.823**	1	-
ICM	0.133*	-0.108	0.205**	0.408**	-0.123	-0.121	0.263**	0.379**	0.637**	-0.621**	1

Table 1: Pearson correlation coefficient as calculated from multiple regression. Parameters marked with '*' or '**' are significantly linearly correlated with a significance level of 0.05 and 0.01, respectively. Abbreviations used in the table: medial-lateral COP component = ML, anterior-posterior COP component = AP, lumbar curvature = LC, sample entropy = SaEn, standard deviation = SD and in-chair movement frequency = ICM.

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