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Gait variability measurements in lumbar spinal stenosis patients: part A. Comparison with healthy subjects

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Abstract
The objective of this study is to compare the gait variability of patients with lumbar spinal stenosis (experimental group) with healthy individuals (control group). The hypothesis is that the preoperative gait variability of the experimental group is higher than the control group. The experimental group consisted of 35 adults (18 males, 17 females). The subjects of the experimental group suffered exclusively from spinal stenosis. The patients were determined by MRI scans. A tri-axial accelerometer sensor was used for the gait measurement, and differential entropy algorithm was used to quantify the gait acceleration signal. The Oswestry Low Back Pain Questionnaire was used to determine the condition on the day of the measurement. Receiver operating characteristic (ROC) was utilized to assess the diagnostic value of the method and determine a cut-off value. There is a statistically significant difference between gait variability in the control group and the experimental group. ROC analysis determines a cut-off differential entropy value. The cut-off value has a 97.6% probability of separating patients with spinal stenosis from healthy subjects. The Oswestry Low Back Questionnaire is well correlated with the spectral differential entropy values.

Keywords: variability, differential entropy, accelerometer, gait analysis, Oswestry Low Back Questionnaire, movement disorders, spine diseases, lumbar spinal stenosis

(Some figures in this article are in colour only in the electronic version)
1. Introduction

Human walking patterns are different. Each person’s gait kinematic and kinetic quantities are assumed to be periodic (Perry 1992, Cappozzo et al 1975) or pseudoperiodic (Pecoraro 2006) and determined by the body characteristics and the personal ability to control the gait. In the case of neuromuscular and musculoskeletal pathologies or injuries, these movements may not be periodic and they may result in increased gait instability.

Lumbar spinal stenosis (LSS) is defined as any narrowing of the lumbar spinal canal, nerve root canal or intervertebral foramina (Arnoldi et al 1976). LSS patients exhibit leg pain in approximately 90% of cases (Turner et al 1992). There have been many studies in the literature regarding LSS diagnostic tools. The most widely researched imaging methods are magnetic resonance imaging (MRI), computer tomography and myelography (Fritz et al 1998). Both CT and MRI have the advantage of allowing direct visualization of both central and lateral canals (Fritz et al 1998). MRI has the added benefit of soft tissue visualization (Kurz and Dvorak 1996). Other commonly used and recommended outcome measurement tools used for assessing the disabling effects of lumbar spinal disorders in the literature are the Oswestry Low Back Pain Questionnaire and the Roland Morris Disability Questionnaire (Fairbanks et al 1980, Deyo et al 1998, Doleys et al 1997, Turk and Marcus 1994).

The purpose of this study was to determine the effect of LSS on gait variability. Variability exists in human gait from one stride to another, the so-called stride-to-stride variability (Hausdorff et al 1995, Hausdorff 2005). Gait variability is a quantifiable feature of walking that is altered—both in terms of magnitude and dynamics—in clinically relevant syndromes such as falling, frailty and neuro-degenerative diseases (Hausdorff 2005). Stride intervals become more uncorrelated (random) in elderly subjects, patients with Huntington’s disease (Hausdorff et al 1997), Parkinson disease (Frenkel-Toledo et al 2005) and healthy people walking in time with a metronome (Hausdorff et al 1996). It has been suggested that a decrease in signal regularity may provide an indication of impaired functional capacity (Kavanagh et al 2005). LSS-affected individuals, in general, tend to be older and have a prolonged history of low back pain (Turner et al 1992, Katz et al 1994, 1995). Leg pain is reported in approximately 90% of cases (Turner et al 1992) and may be unilateral or bilateral. Chronic compression of the spinal nerve roots can lead to symptoms of radicular pain and sensory, motor and/or reflex changes in one or both lower extremities (Penning 1992, Oriel et al 1993). Neurogenic claudication, defined as poorly localized pain, paresthesias and cramping of one or both lower extremities of a neurologic origin, which is brought on by walking and relieved when sitting (Stucki et al 1992), frequently accompanies LSS (Turner et al 1992, Katz et al 1994, 1995). It has been reported that walking tolerance (i.e. the ability to endure the stresses of normal walking) can become substantially limited because of neurogenic claudication (Rausching 1993, Amundsen et al 1995). The general hypothesis is that a person with a gait-affecting pathology will exhibit disruptions in his normal gait patterns, when subjected to unexpected discomfort/pain. In other gait variability studies, it was hypothesized that the inability to perceive painful or uncomfortable stimuli would reduce the appropriate corrections, thus resulting in reduced gait variability. If the pain is not expected (normally in gait, acute pain is unexpected, otherwise the subject develop walking strategies that would help them avoid the pain), then the periodicity of the gait would change. Since, the literature supports that LSS patients suffer from acute pain, the working hypothesis in this paper is that LSS patients exhibit different gait variability.

Currently, the most commonly used method in gait variability studies is approximate entropy (Arif et al 2002, 2004, Kurz and Stergiou 2003, Karmakar et al 2007, Khandoker et al 2008, Georgoulis et al 2006). Approximate entropy is a technique that can be used to quantify irregularity or variability of the time series based on statistics (Pincus 1991). ApEn
is dependent on two parameters: \( m \) is a scale parameter (associated with the length of the pattern) and \( r \) is a parameter that sets the interval within which the pattern is considered similar (i.e. \( r \) turns a continuous variable to a discrete binary variable). ApEn is the log probability that a series of data points (\( m \) in length)—a certain distance (\( r \)) apart—exhibit similar relative characteristics on the next incremental comparison (\( m+1 \)) within the state space (Pincus and Goldberger 1994). Typical values are \( m = 2 \), and \( r = 0.15–0.2 \). ApEn is loosely related to statistical entropy introduced by Shannon (1948), in the sense that higher values of Shannon’s statistical entropy and ApEn are associated with higher variability or irregularity, and lower values close to zero represent smaller variability. Another similarity is that Shannon’s entropy is associated with partitions of discrete variables, and ApEn in essence with the use of the \( r \)-parameter, generates a binary variable (either the pattern is within or outside). Apart from those similarities, there are also significant differences in the calculation procedure (which is beyond the scope of this work); one of them is the upper bound of the value domain (Shannon’s upper bound is \( \log(N) \) where \( N \) is the number of states, ApEn upper bound is 2).

Hoyer et al (2005) proposed a method for monitoring complex back movement behaviour and its alterations due to low back pain and age based on Shannon’s entropy and mutual information. While Shannon’s entropy has been extended to continuous variables (Papoulis 1984) and is widely referred to as differential entropy, it has never been previously used in orthopedics.

Accelerometry has been proven reliable and highly applicable to a clinical setting (Willemsen et al 1990, Aminian et al 1998 and Henriksen et al 2004), but has never been used for LSS diagnosis. Accelerometry compared to stereophotogrammetry and dynamometry offers increased measurement volumes (Pecoraro 2006). A wide range of measurements, including classification of movements, assessment of physical activity level, estimation of metabolic energy expenditure, assessment of balance, gait and sit-to-stand transfers, can be reliably obtained using a single tri-axial accelerometer worn at the waist (Mathie et al 2004). This work investigates the difference in gait variability of LSS patients and healthy individuals through entropic analysis of the vertical gait acceleration signal.

2. Methods

2.1. Subject selection criteria

Two groups participated in this study. The experimental group consisted of subjects diagnosed with spinal stenosis and the control group consisted of healthy subjects with no history of neuromuscular and musculoskeletal pathology or injury. The experimental group’s subjects were diagnosed with spinal stenosis, without any other neuromuscular and musculoskeletal pathology or injury, using MRI scans. Originally, the anterior–posterior (AP) diameter of the spinal canal on the myelography was used as the basis for diagnosis (Verbeist 1955). An AP diameter of less than 10 mm was considered an ‘absolute stenosis,’ and a diameter of 10–12 mm a ‘relative’ stenosis (Tuite et al 1994). On the CT or MRI, the cross-sectional area of the dural sac was reported as a more reliable diagnostic measurement and a cross-sectional area of greater than 100 mm\(^2\) as normal, 76–100 mm\(^2\) as moderately stenotic and less than 76 mm\(^2\) as severely stenotic (Schonstrom et al 1985).

Oswestry Disability Questionnaire (ODQ) forms were completed. A \( t \)-test was performed in order to determine statistically significant differences in the mean values of age, height and weight between experimental and healthy groups. A chi-square test was used to verify that the control and experimental group had similar gender proportions (table 1).
Medical staff were responsible for interviewing the subjects and recording contact details, height, weight, age and medical history. All subjects signed an informed consent according to the University Institutional Review Board.

2.2. Device description

The measurement device consisted of a tri-axial digital output linear accelerometer LIS3LV02DQ, a micro-controller, a voltage regulator (MC33269D3.3), a 4 MB flash memory, a transceiver and a battery. The measurement device was based on an 8-bit micro-controller, ATTINY2313. The device dimensions were 125 × 65 × 25 mm and it weighted 150 g (including a 9 V battery). Low weight was important for minimizing interference in the measurement. The maximum sampling rate of the measurement device was 2000 Hz, and the MEMS accelerometers were able to measure acceleration up to ±2 g. The sampling frequency in this study was selected at 128 Hz, after examining the frequency content of normal walking at a sampling rate of 256 Hz, 512 Hz and 1024 Hz. The studies showed that sampling frequencies higher than 1024 Hz were not used because frequency response of MEMS accelerometers is very poor beyond 1000 Hz, and therefore the gait accelerations measurements would have been questionable. Most gait analysis studies usually sample at 100–500 Hz. Earlier studies suggested higher sampling rates and then performed low pass filtering of the signal (usually a first or second class Butterworth filter (Willemsen et al 1990 and Kavanagh et al 2005), while more recent work suggests lower sampling rates without any filtering (Arif et al 2002, 2004 and Henriksen et al 2004).

The data were transferred to a PC via an RS232 port. The data were stored on a PC in ASCII tagged format for easy retrieval. An example of a typical raw accelerometer signal is presented in figure 2. In this study, although all accelerations were recorded, only vertical z-axis acceleration was used.

An analysis of the combined accelerations (x, y and z) was not conducted due to limitations of the measurement protocol. The measurement protocol did not specify a standardized gait velocity (on the x-axis—anterior–posterior) during the measurement. As a result, the gait cycle length on the x-axis was different because it depended on gait velocity. Also the acceleration on the y-axis (transverse or medio-lateral) was not considered suitable for analysis. Slight gait deviations from a straight line could induce perturbations in the medio-lateral acceleration. Despite the fact that these deviations are not necessarily attributed to pathology, they contributed to gait variability. The vertical (z) displacement was selected because it minimized the issues of the other directions. More specifically, the vertical travel distance in a gait cycle was considered constant regardless of the gait velocity. Additionally, the gait variability in the z-axis was not considered to be affected from gait deviations from a straight line. Finally, the z-axis was selected because of its predominant frequency which is double the respective frequency of the y-axis. In each gait cycle (left and right step) the

### Table 1. Summary statistics of body type parameters and statistical comparison between groups.

<table>
<thead>
<tr>
<th></th>
<th>Healthy</th>
<th>LSS patient</th>
</tr>
</thead>
<tbody>
<tr>
<td>Sample size</td>
<td>Mean</td>
<td>Standard deviation</td>
</tr>
<tr>
<td>Age (years)</td>
<td>35 51.06 11.74</td>
<td>35 50.66 12.91</td>
</tr>
<tr>
<td>Height (cm)</td>
<td>35 166.40 8.88</td>
<td>35 167.45 8.03</td>
</tr>
<tr>
<td>Weight (kg)</td>
<td>35 75.28 11.86</td>
<td>35 74.68 10.89</td>
</tr>
<tr>
<td>Gender (men)</td>
<td>– –</td>
<td>– –</td>
</tr>
</tbody>
</table>
Centre of Gravity moves vertically twice and laterally only once. As a result, the frequencies are spread along a wider range (compared to the y-axis). In the future, there is intention of developing a measurement protocol involving a treadmill that will allow analysis of combined accelerations.

2.3. Gait variability analysis method

The differential entropy of the gait acceleration signal was calculated using the method that was described by Papadakis and Christakis (2008). Differential entropy is an extension to
Shannon’s entropy to continuous variables. Differential entropy is defined (Papoulis 1984) as
\[ h(x) = - \int f(x) \cdot \log_e(f(x)) \, dx \] (1)
where \( f(x) \) is the probability density function of continuous variable \( x \) (\( x \) belongs \([a, b]\)).

In most cases it is very difficult/impossible to analytically determine \( f(x) \); however it is possible to calculate approximately the entropy of a continuous variable using a discrete (numerical) approximation (Papoulis 1984).

By the mean-value theorem there exists a value \( x_i \) in each bin such that
\[ \int_{i\delta}^{(i+1)\delta} f(x) \, dx = f(x_i) \delta. \] (2)
Then the integral of \( f(x) \) can be approximated (in the Riemannian sense) by
\[ \int_{-\infty}^{\infty} f(x) \, dx = \lim_{\delta \to 0} \sum_{i=-\infty}^{\infty} f(x_i) \delta. \] (3)
By denoting
\[ H_\delta = - \sum_{i=-\infty}^{\infty} \delta \cdot f(x_i) \cdot \log_e(\delta \cdot f(x_i)) \] (4)
and expanding the logarithm, equation (4) becomes
\[ H_\delta = - \sum_{i=-\infty}^{\infty} \delta \cdot f(x_i) \log_e(\delta) - \sum_{i=-\infty}^{\infty} \delta \cdot f(x_i) \cdot \log_e(f(x_i)). \] (5)
Given that \( f(x) \) satisfies the conditions of a probability density function, the following is true as \( \delta \to 0 \):
\[ \int_{-\infty}^{\infty} f(x) \, dx = 1 = \lim_{\delta \to 0} \sum_{i=-\infty}^{\infty} \delta \cdot f(x_i). \] (6)
And therefore the second term in equation (5) is
\[ - \sum_{i=-\infty}^{\infty} \delta \cdot f(x_i) \log_e(\delta) \to - \int f(x) \cdot \log_e(f(x)) \, dx. \] (7)
However, as bin length \( \delta \) tends to zero \( \delta \to 0 \), \( \log \delta \to -\infty \), and equation (1) becomes
\[ h(x) = - \int f(x) \cdot \log_e(f(x)) \, dx = \lim_{\delta \to 0} [H_\delta + \log_e(\delta)]. \] (8)
Therefore, in order to obtain the entropy of the continuous variable, the following formula (equation (9)) is used (Papoulis 1984):
\[ h(x) \approx - \sum_{i=-\infty}^{\infty} \delta \cdot f(x_i) \cdot \log_e(f(x_i)) + \log_e(\delta) = H_\delta + \log_e(\delta). \] (9)
In order to obtain the differential entropy of a continuous variable \( h(x) \), the Shannon’s entropy of the quantized variable \( H_\delta \) needs to be corrected by the quantization factor \( \delta \). Therefore, the above approximation of the continuous variable differential entropy is invariant to the discretization factor \( \delta \). This is of significant benefit compared to the ApEn or multiscale entropy that are depended on proximity parameters (i.e. the parameter \( r \)).

In order to detect frequency irregularities in a time series, the power spectrum of a signal was obtained. The power spectrum \( \text{PS}(\phi_i) \) of the acceleration signal is obtained, where \( \phi_i \) is the
ith frequency component (the 0 component is the DC component). Generally, each frequency component is $\varphi_i = i \Delta \varphi$ (Hz), where $\Delta \varphi$ is the frequency interval of the power spectrum in hertz. The power spectrum is normally obtained in the form of a vector, in a similar manner that the continuous variable $x$ is quantized into the variable $x_i$. The power spectrum is divided by the integral of the power spectrum:

$$PS'(\varphi_i) = \frac{PS(\varphi_i)}{\int_0^{f_s} PS(\varphi) d\varphi}$$  \hspace{1cm} (10)

where $f_s$ is the sampling frequency.

The differential entropy is then applied to the normalized power spectrum $PS'(\varphi_i)$—(equation (11)):

$$h(x) \approx - \sum_{i=0}^{n} \Delta \varphi \cdot PS'(\varphi_i) \cdot \log_e(PS'(\varphi_i)) + \log_e(\Delta \varphi).$$  \hspace{1cm} (11)

If the signal is periodic (low variability in the frequency domain), then there will be a predominant frequency component and therefore lower differential entropy values will be obtained. On the other hand, if a signal is random (e.g. white noise), then more frequency components with relatively high power are selected and therefore higher differential entropy values will be obtained. The range of values for the differential entropy of the normalized power spectrum is $(\log_e(\Delta \varphi), \Delta \varphi \log_e(n) + \log_e(\Delta \varphi))$. Therefore, a low spectral differential entropy value is associated with periodic gait acceleration time series, while high spectral differential entropy values are associated with irregular gait acceleration time series.

Depending on the logarithmic base, differential entropy is measured bits for log base 2, nats for log base $e$ and bans in Log$_{10}$. The selection of the base will not change the results qualitatively. The base that was selected in this study was $e$, and therefore the units of the differential entropy are in nats.

2.4. Measurement procedure

Measurements were performed in the morning. Subjects wore light clothes and thin shoes. Medical staff ascertained that the subjects were calm. The measurement device was attached to an elastic belt. The operator of the measurement device placed the belt near the fifth lumbar vertebrae (figure 1). The measurement device measured the approximate gait acceleration of the centre of gravity (COG) of the subject body. It is not possible to measure the exact acceleration of the COG, because the subject’s COG may be inside the body.

The low weight of the measurement device minimized the influence on the subjects’ walking. In general, every precaution was taken in order to minimize distraction for the subjects during the measurements.

All subjects were instructed to walk along a 40 m straight hospital level walkway at a self-selected walking speed.

Gait acceleration signals were obtained for each axis at a sampling rate of 128 Hz. The measurement duration was 30 s in order to obtain a time series that could be truncated and still produce a power spectrum with a frequency component resolution $(df)$ lower than 0.1 Hz. The signal was truncated before processing. The first and last two (2) gait cycles were removed, because it was deemed that acceleration and deceleration would contribute to variability.

The vertical gait acceleration time series were examined for the convergence of differential entropy values (see figure 3). Differential entropy values converged after approximately
15 s, in most cases. The 30 s duration and the walking distance 40 m were significantly greater than those in similar studies in the literature (Henriksen et al 2004).

The subjects were asked to fill in the the ODQ. ODQ is a disease-specific self-reported level of health status (Fairbanks et al 1980, Fritz et al 1998). The ODQ measures the subject’s disability in 10 areas (standing, sitting, walking, sleeping, travelling and weight lifting, sexual and social behaviour, and the pain felt at the moment of the measurement procedure). The measurement is in the form of 6-level scale from 0 to 5 (0 being the less painful/disabling, 5 being the most painful/disabling). In order to obtain the ODQ score, the individual area subscores are added and then the total is multiplied by 100. ODQ values near 0 are less painful/debilitating, while ODQ values near 100 aim to describe painful/disabling conditions. A prolonged history of low back pain is reported in many LSS studies (Turner et al 1992, Katz et al 1994, 1995).

The measurements were performed on the premises of the University of Crete Hospital with the aid of the medical staff of the Orthopaedic Department of the University Hospital, in Heraklion, Crete.

2.5. Statistical analysis

A t-test is used to compare the spectral differential entropy values between the two groups (null hypothesis is that the mean values are equal). A receiver operating characteristic (ROC) analysis is used to determine the optimal cut-off differential entropy point for the separation of patients and control subjects and estimate the percentage of true positives.

In order to assess the diagnostic usefulness of the method, the likelihood ratio (LR) was used (Sackett et al 1992, Simel et al 1991). The positive likelihood ratio (PLR) is defined (sensitivity/(1 − specificity)). A positive LR expresses the probability that a positive test result would be expected in a patient with (as opposed to without) spinal stenosis (Fritz et al 1998). A high positive LR (e.g 5.0) indicates a test in which a positive result is helpful for ruling in the diagnosis. The negative likelihood ratio (NLR) is defined ((1 − specificity)/sensitivity). A NLR expresses the probability that a negative test result would be expected in a LSS patient. A small NLR (<0.3) is associated with tests in which a negative result is helpful in ruling out a diagnosis (Riegelman and Hirsch 1996).
Spectral differential entropy measures and the relationship between the patient’s disability rate and pain scale were tested through Spearman’s correlation coefficient. A multiple regression model was constructed based on Oswestry subscores.

SPSS 15.0 and the R project for statistical computing v.2.8.0 were used for statistical analysis. A significance level of $a = 0.05$ was used.

3. Results

3.1. Subjects

The experimental group consisted of 35 adults (18 males, 17 females; age 50.65 ± 12.92 years, height 167.45 ± 8.04 cm, 74.69 ± 10.90 kg, BMI: 26.75 ± 4.28 kg m$^{-2}$). The subjects of the experimental group suffered exclusively from spinal stenosis and were able to walk for at least 40 sec. The control group consisted of 35 healthy adults (16 males, 19 females, age 51.057 ± 11.745 years, height: 166.4 ± 8.88 cm, 75.29 ± 11.86 kg, BMI: 27.16 ± 3.5931 kg m$^{-2}$) with no history of neuromuscular, musculoskeletal, respiratory or cardiological pathology or injury. MRI scans, clinical examinations and the Oswestry questionnaire were used for the diagnosis.

Table 2 presents the spectral differential entropy values for the experimental and the control groups. Figure 4 presents a dot plot of the spectral differential entropy values and the cut-off value.

3.2. ROC analysis

Figure 5 presents the ROC. To obtain the ROC, the differential entropy values have been ordered with respect to magnitude. A series of cut-off values was created, by selecting midpoints through the ordered differential entropy values. For each cut-off value, $(1 - \text{specificity})$ and $(\text{sensitivity})$ values are computed as percentages based on the true positives.
Figure 5. Receiver operating characteristics curves: showing the true positive (sensitivity) and false positive rates \(1 - \text{specificity}\) for various thresholds using the differential entropy.

Table 2. Spectral differential entropy values.

<table>
<thead>
<tr>
<th>Experimental group</th>
<th>Control group</th>
</tr>
</thead>
<tbody>
<tr>
<td>Subject no.</td>
<td>Differential entropy</td>
</tr>
<tr>
<td>------------------</td>
<td>----------------------</td>
</tr>
<tr>
<td>E1</td>
<td>1.510</td>
</tr>
<tr>
<td>E2</td>
<td>0.182</td>
</tr>
<tr>
<td>E3</td>
<td>0.518</td>
</tr>
<tr>
<td>E4</td>
<td>1.583</td>
</tr>
<tr>
<td>E5</td>
<td>0.058</td>
</tr>
<tr>
<td>E6</td>
<td>0.206</td>
</tr>
<tr>
<td>E7</td>
<td>0.432</td>
</tr>
<tr>
<td>E8</td>
<td>0.403</td>
</tr>
<tr>
<td>E9</td>
<td>1.227</td>
</tr>
<tr>
<td>E10</td>
<td>1.311</td>
</tr>
<tr>
<td>E11</td>
<td>1.71</td>
</tr>
<tr>
<td>E12</td>
<td>1.317</td>
</tr>
<tr>
<td>E13</td>
<td>1.785</td>
</tr>
<tr>
<td>E14</td>
<td>0.321</td>
</tr>
<tr>
<td>E15</td>
<td>1.433</td>
</tr>
<tr>
<td>E16</td>
<td>0.722</td>
</tr>
<tr>
<td>E17</td>
<td>0.695</td>
</tr>
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<td></td>
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</tr>
</tbody>
</table>

and false negatives. Figure 5 presents the coordinates of each cut-off value in the 2D space of \(1 - \text{specificity}\) and \text{sensitivity}. Each point has a distance from the diagonal (the non-discrimination line). The point with the greater distance from the diagonal was selected and indicates the optimum tradeoff between true positives and false negatives.
The ROC analysis determined the optimal cut-off value as 0.06 nats. Spectral differential entropy values greater than 0.06 nats (i.e. higher irregularity) indicate LSS. The cut-off entropy value (0.06 nats) yields to 97.1% sensitivity and 80.0% specificity. ROC analysis estimates a 97.1% probability for correct identification of patients and an 80.0% probability for correct identification of healthy subjects. According to ROC analysis, the area under the curve is 97.6%; therefore, the spectral differential entropy index has a 97.6% probability for distinguishing between patients with spinal stenosis and healthy subjects.

The positive likelihood ratio (PLR) (sensitivity/(1 − specificity)) at the cut-off value is 4.86, and the negative likelihood ratio (NLR) is 0.21. Therefore, the LR values of gait variability (through the spectral differential entropy index) suggested that the method has a potentially diagnostic value.

3.3. Oswestry and differential entropy correlation

The spectral differential entropy values of the experimental group are higher than those of the control group. The difference is statistically significant ($t_{68} = -10.291, p < 0.001$). Therefore, the LSS patient’s gait exhibits more irregularity and variability compared to healthy patients.

The Spearman correlation coefficient between spectral differential entropy values and ODQ scores for the experimental group is 0.654. Figure 6 presents the Oswestry values with respect to the spectral differential entropy of the $z$-axis. Oswestry values higher than 40 appear to be significantly affected by the differential entropy values. Oswestry values lower that 40 appear to be associated with low values of differential entropy.

The sitting, standing and walking ability Oswestry subscores were also investigated. It was found that the Spearman correlation coefficient between spectral differential entropy values and Oswestry subscores sum for the experimental group is 0.658. Therefore, the remaining Oswestry subscores only have a minor negative effect.

4. Discussion

4.1. Gait variability

Suda et al (2002), tried to quantify the gait disturbances caused by spinal diseases. They reported that spinal disease can affect leg function. This is consistent with the findings in this paper. The null hypothesis was rejected (i.e. the experimental group’s differential entropy values are different to the corresponding control group’s values), i.e. the gait variability of healthy subjects is different to that of LSS affected subjects. The difference is statistically
significant. Therefore, there is a measurable difference in gait variability of healthy subjects and LSS subjects. The gait irregularity is attributed to the low walking tolerance and radicular pain, which are common clinical symptoms in LSS patients (Stucki et al 1994, Turner et al 1992, Katz et al 1994, 1995, Rausching 1993, Amundsen et al 1995). More specifically, the low walking tolerance and radicular pain compel the subject to compensate by adjusting the gait pattern. This leads to increased gait variability.

In the literature, there have been conflicting reports regarding the trend of gait variability in pathological conditions. The increased gait variability observed in this paper is consistent with the findings of Arif et al 2002, 2004, Kurz and Stergiou 2003, Karmakar et al 2007 and Khandoker et al 2008. It has been reported (Arif et al 2002, 2004, Kurz and Stergiou 2003, Karmakar et al 2007) that with increasing age (and therefore loss of neuromuscular control) the gait variability increases. Similarly, it has been reported that fall risk subjects indicate higher minimum foot clearance variability (Khandoker et al 2008).

Georgoulis et al (2006) observed that an anterior cruciate ligament (ACL)-deficient knee exhibits more regular and less variable patterns than an intact knee. However, ACL is a condition in which the subject is able to adjust his/her walking strategies, in order to compensate for the perceived instability. As a result, the subject walks at a pace and with a style that protects the injured member. In contrast, LSS subjects are only able to react to the radicular pain which is manifested as poorly localized pain (Stucki et al 1994). The reaction to LSS-induced pain leads to irregular and unpredictable movements, thus increasing the variability. Therefore, LSS-affected patients compared to ACL-affected patients exhibit radically different gait variability compared to healthy subjects due to the walking strategies that the ACL patients are able to apply.

An additional finding of Georgoulis was that ApEn values for injured subjects significantly increased with increasing walking speed. As the ACL-affected patient is forced to increase the velocity beyond the comfort zone, he/she loses the ability to apply the strategy that protects the injured member. As a result, the increased pain leads to irregular movements and increased gait variability, in a way similar to LSS-affected patients. Changes in gait variability are also consistent with the reports by Costa et al (2003). Costa et al reported that unconstrained free walking has more complex dynamics followed by fast walking and finally slow walking. Therefore, in general, gait variability is expected to increase as the subject moves away from the comfort zone and is expected to decrease if the subject is able to devise and implement successful control strategies to prevent pain/injury or fall.

Gradually progressing or chronic conditions allow an individual to adapt their gait patterns. Gates and Dingwell (2007) reported that peripheral sensory feedback due to diabetes retained long-range correlations in their stride intervals comparable to healthy individuals. Dingwell and Cavanagh (2001) reported small but statistically significant increases in the variability of peripheral neuropathy patients’ movement patterns compared to healthy individuals. Both authors attributed the lack of significant differences in long-range correlation to adaptation effects. Peripheral neuropathy is a slow advancing disease, and these patients have been living with significant and progressive sensory loss for many years.

4.2. ROC analysis

ROC analysis was performed. A cut-off value equal to 0.06 nats was determined, with 97.1% probability for correct identification of patients and 80.0% probability for correct identification of healthy subjects. It was estimated that the proposed method has 97.6% probability for correctly distinguishing between patients suffering of spinal stenosis and healthy subjects. The sensitivity and specificity of the results are comparable to a Myelography and CT (Fritz
Table 3. Typical values of sensitivity and (1 − specificity) of myelography (Bell et al 1984, Siebus 1988), CT (Bell et al 1984, Schonstrom et al 1985) and MRI (Modic et al 1984, Boden et al 1990).

<table>
<thead>
<tr>
<th>Method</th>
<th>Sensitivity</th>
<th>1 − Specificity</th>
</tr>
</thead>
<tbody>
<tr>
<td>Myelography</td>
<td>0.77–0.78</td>
<td>0.28</td>
</tr>
<tr>
<td>CT</td>
<td>0.77–0.88</td>
<td>0.17–0.20</td>
</tr>
<tr>
<td>MRI</td>
<td>0.81–0.97</td>
<td>0.00–0.06</td>
</tr>
<tr>
<td>Differential entropy</td>
<td>0.97</td>
<td>0.2</td>
</tr>
</tbody>
</table>

et al 1998, Siebus et al 1988, Bell et al 1984), and an MRI which is considered the gold standard (see table 3). The differential entropy method’s sensitivity and (1 − specificity) values were promising. It has to be noted that results of this method are only applicable to a group consisting solely of LSS and healthy subjects.

Although the LR values are not directly comparable, because gait variability cannot on its own differentiate between pathologies, Fritz et al (1998) reported on the diagnostic value of imaging studies for LSS. Fritz et al (1998) report that a high PLR (8.1–16.2) and small NLR (0.03–0.19) for MRI suggest that this test is excellent both for ruling in and ruling out a diagnosis of LSS. The PLR of differential entropy is 4.86, and the NLR is 0.21. Therefore, the method may have some usefulness as an initial screening of subjects before proceeding to more costly and time-consuming methods as MRI.

4.3. Oswestry and differential entropy

In this work, the working hypothesis is that the acute radicular pain increases the gait variability of the LSS subject. The Spearman correlation test yielded $r^2 = 0.654$; therefore’ the spectral differential entropy values correlate well with the Oswestry Low Back Pain Questionnaire. This highlighted the connection between gait variability and the self-reported level of health status—i.e. subjects with high disability values are expected to exhibit greater gait variability.

Two distinct relationships between Oswestry and differential entropy were observed with respect to a certain threshold (Oswestry value = 40). All Oswestry values below the threshold exhibited a similar differential entropy value, which was near the differential entropy values computed for healthy patients. Oswestry values higher than the threshold exhibited a linear relationship with differential entropy values. This is attributed to the Oswestry being a patient-centred outcome that reports generally on the subject’s health status. Higher Oswestry values indicate higher perceived disability in an individual and more pain. Acute pain increases the gait variability in the gait. The observed threshold might represent conditions beyond which pain becomes severe even over short distances.

It was also observed that the sum of Oswestry subscores pertaining to walking ability, standing and sitting correlated slightly better to gait variability. The three subscores account for approximately 30% of the Oswestry score. Since the three Oswestry subscores are directly relevant to gait, this is an indication that the differential entropy index is able to reflect pathologies related to gait.

4.4. Device and method

Accelerometry and the differential entropy algorithm were used for the first time in orthopaedics and LSS-affected patients. Accelerometry has been proven reliable and highly applicable to a clinical setting (Willemsen et al 1990, Aminian et al 1998 and Henriksen et al 2004). Trunk gait accelerometry was reported as able to reveal even minor changes in normal

Gait analysis using accelerometry and differential entropy has the added advantage of causing less stress to the subject, because the analysis can be conducted in a short time and the subject is only required to walk as usual. It permits objective and quantitative evaluation of the gait characteristics in patients with LSS and is useful for the evaluation of responses to surgical treatment in these subjects. The proposed method is also painless, low cost, non-invasive, without radiation or chemical substances, and the objective index that corresponds to gait irregularity may be computed instantly.

The use of a 40 m walkway is one of the limitations of the measurement protocol of the method. An obvious solution is the use of a treadmill. The use of the treadmill would also enable the standardization of the gait velocity. Another limitation was the small number of participants, due to the screening of patients with neuromuscular and musculoskeletal injury different to LSS. The screening process also excluded patients with respiratory/cardiological pathology.

5. Conclusions

The purpose of this study is to determine the effect of LSS on gait variability. The working hypothesis was that LSS patients would exhibit higher gait irregularity compared to healthy subjects due to the LSS’s common clinical symptoms (i.e. acute radicular pain). In the examined sample, there was statistically significant difference in gait variability between healthy subjects and LSS subjects.

ROC analysis was performed. A cut-off value equal to 0.06 nats was determined. The PLR and the NLR indicated the possible diagnostic value of the method. This work indicates that patients with spinal stenosis exhibit higher irregularity in gait patterns than healthy subjects. The results of this paper apply only to groups of healthy and LSS suspected patients (i.e. the method would not be possible to discriminate between other gait affecting pathologies). The proposed method maybe used as a cost-effective first-stage screening method. Further work and a higher number of samples are required to improve the performance of the method.

According to the Spearman correlation test, the spectral differential entropy values correlate well with the Oswestry Low Back Pain Questionnaire. This highlights the relationship between the gait irregularity and the self-reported level of health status. It is proposed that radicular pain is the source of gait variability of the LSS subject.

Gait analysis using accelerometry and differential entropy has the advantage of causing less stress to the subject, because the analysis can be conducted in a short time and the subject is only required to walk as usual. It permits an objective and quantitative evaluation of the gait characteristics in patients with LSS and is useful for the evaluation of responses to surgical treatment in these subjects.

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