A Model-based Approach for Estimation of Changes in Lumbar Segmental Kinematics Associated with Alterations in Trunk Neuromuscular Strategy

Short Communication

Iman Shojaei[1], Navid Arjmand[2], Judith R. Meakin[3], and Babak Bazrgari[1]

[1] F. Joseph Halcomb III, M.D. Department of Biomedical Engineering, University of Kentucky, Lexington, KY 40506, USA

[2] Department of Mechanical Engineering, Sharif University of Technology, Tehran, Iran

[3] School of Physics and Astronomy, University of Exeter, Physics Building, Stocker Road, Exeter EX4 4QL, UK

Corresponding address: Babak Bazrgari, F. Joseph Halcomb III, M.D. Department of Biomedical Engineering, University of Kentucky, 514E Robotic and Manufacturing Building, Lexington, KY 40506.

Phone: (859) 257-1379. E-mail: babak.bazrgari@uky.edu. Fax: (859) 257-1856

Abstract Word Count: ~ 240

Main Text Word Count: ~ 2500

Abstract

The geometrical information from imaging, if combined with optimization-based methods of neuromuscular assessment, may provide a unique platform for personalized assessment of trunk neuromuscular behavior. Such a method, however, is feasible only if differences in lumbar spine kinematics due to differences in trunk neuromuscular behavior can be captured by the current imaging techniques. A finite element model of the spine within an optimization procedure was used to estimate segmental kinematics of lumbar spine associated with five different hypothetical trunk neuromuscular strategies (TNSs). Each TNS optimized one aspect of lower back biomechanics and was assumed to either represent the TNS of asymptomatic persons or a neuromuscular abnormality. For each TNS, the segmental kinematics of lumbar spine was estimated for a single static trunk flexed posture involving, respectively, 40° and 10° of thoracic and pelvic rotations. Minimum changes in the angular and translational deformations of a motion segment with alterations in TNS ranged from 0° to 0.5° and 0 mm to 0.04 mm, respectively. Maximum changes in the angular and translational deformations of a motion segment with alterations in neuromuscular strategy ranged from 2.4° to 7.5° and 0.11 mm to 0.39 mm, respectively. The differences in kinematics of lumbar segments between each combination of two TNSs in 97% of cases for angular deformation and 55% of cases for translational deformation were within the reported accuracy of current imaging techniques. Combined imaging and computational modeling appears to have potentials for predicting alterations in neuromuscular strategies.

Keywords: Muscle forces and spinal loads, Finite element analysis, optimization procedures, Trunk neuromuscular strategies, Lumbar segmental kinematics, Image-based modeling

Introduction

Neuromuscular control of spinal equilibrium and stability changes in the presence of pain or following exposure to known risk factors for low back pain (LBP) (Muslim et al., 2013; Radebold et al., 2000; Radebold et al., 2001; Toosizadeh et al., 2013). Such alterations may cause deformations and/or forces in lower back tissues such that exceed injury/pain thresholds instantaneously or cumulatively (Adams et al., 2013; Coenen et al., 2014; Marras et al., 2001; Panjabi, 1992a, b). Despite such a significant role, the current methods for assessment of trunk neuromuscular behavior are limited. Kinematic measures of lumbo-pelvic coordination, though capable of distinguishing patients with LBP from controls (Vazirian et al., 2016), do not provide much information about abnormalities in trunk neuromuscular control. Specifically, neuromuscular redundancy in control of lumbo-pelvic motion as well as individual variability in mechanical behavior of passive lumbar tissues hinder relating measured kinematics data to trunk neuromuscular control. The commonly used surface electromyography (EMG)-based methods for the assessment of trunk neuromuscular behavior, on the other hand, can only provide information about the activity of superficial trunk muscles. Further, the literature on EMG-based assessment of neuromuscular abnormalities in patients with LBP is not consistent (van Dieën et al., 2003) which has been attributed to normalization of EMG values to sub-maximal contractions due to unwillingness and/or inability of patients with LBP to generate maximum voluntary contractions (van Dieën et al., 2003). Finite element and multi-joint biomechanical models of the spine with detailed musculature have also been developed and used for general assessment of trunk neuromuscular behaviors (Arjmand and Shirazi-Adl, 2006a, b; Dreischarf et al., 2014; Ezquerro et al., 2004; Hughes, 2000; Stokes and Gardner-Morse, 2001). These models often implemented optimization procedures to estimate trunk neuromuscular behavior (Arjmand and Shirazi-Adl, 2006b; Daniel, 2011; Hughes, 2000; Stokes and Gardner-Morse, 2001) and are not suitable for personalized assessment of trunk neuromuscular behavior due to the requirement for a priori knowledge of trunk neuromuscular strategy (e.g., a strategy that minimizes stress in muscles).

Currently, imaging is used to detect structural and geometrical/kinematics abnormalities in the lumbar spine (Fujii et al., 2007; Iwata et al., 2013; Keller et al., 2003; Kjaer et al., 2005; Ochia et al., 2006). The image-based geometrical/kinematics information have also been used for development of geometrically personalized biomechanical models of normal and scoliotic spine (Eskandari et al., 2017; Ghezelbash et al., 2016; Lafon et al., 2010; Petit et al., 2004), biomechanical comparison of healthy and metastatically involved vertebrae (O'Reilly and Whyne, 2008), material sensitivity analysis of intervertebral disc (Fagan et al., 2002), indirect estimation of spinal loads (Shymon et al., 2014), and estimation of elastic modulus of cancellous bone (Diamant et al., 2005). The geometrical information from imaging if combined with optimization-based methods of neuromuscular assessment may provide a unique platform for personalized assessment of trunk neuromuscular behavior. Particularly, it will be possible to use an optimization-based computational model to search for a neuromuscular strategy, that when accounted in the cost function of the optimization-based method, results in lumbar kinematics similar to those obtained from imaging. Such a method, however, is reliable only if differences in lumbar spine kinematics due to differences in trunk neuromuscular behavior can be captured by the current imaging techniques.

Recently, we have used our finite element model of the spine within an optimization procedure to estimate kinematics of lumbar spine that is associated with a trunk neuromuscular strategy (TNS) that minimized sum of squared stress across all trunk muscles (Shojaei et al., 2015). The resultant kinematics were consistent with image-based reports of lumbar spine kinematics of asymptomatic individuals. Using the proposed algorithm, estimation of lumbar segmental kinematics for other hypothetical TNSs that optimize other aspects of lower back biomechanics is possible. Therefore, the objective of this feasibility study is to determine changes in lumbar segmental kinematics due to alterations in TNS and to verify if such changes are within the reported precision of current imaging techniques.

Methods

Five different TNSs, each represented by a distinct cost function for the optimization procedure, were selected and assumed to either represent the TNS of asymptomatic persons or a neuromuscular abnormality that minimizes loading on a specific aspect of lower back tissues (i.e., muscles, ligaments, intervertebral discs, and facet joints). As noted earlier, a neuromuscular strategy associated with the minimum value of sum of squared muscle stresses across the entire trunk muscles resulted in lumbar segmental kinematics consistent with image-based reports of lumbar spine kinematics of asymptomatic individuals, hence, was regarded to represent a normal TNS (Shojaei et al., 2015). On the other hand, abnormal neuromuscular strategies that minimize loads in muscles, ligaments, intervertebral discs, and facet joints were represented by strategies that respectively minimize sum of squared muscle forces across the entire trunk muscles, passive moment, compression, and shearing force at the L5-S1 intervertebral disc. For each TNS, the change in distance between centers of two vertebrae of each motion segment (i.e., translational deformation) as well as changes in their relative angular orientations with respect to each other (i.e., angular deformation) were estimated as lumbar segmental kinematics for a single static trunk flexed posture involving, respectively, 40° and 10° of thoracic and pelvic rotations (i.e., equal to a total lumbar flexion of 40° - 10° = 30°) in the sagittal plane. Forward trunk bending is a common posture used for X-ray imaging of patients with LBP and the specific thoracic and pelvic rotations considered here are the same rotations we used in a recent study for validation of our method (Shojaei et al., 2015).

In the optimization procedure, rather than implementing a force-driven approach for estimation of lumbar segmental kinematics associated with a given TNS, we used our kinematics-driven methods. Such a methodological choice was mainly because of the lower computational cost of kinematics-driven approach. Specifically, the potential neuromuscular strategies searched in the optimization, where a kinematics-driven approach is used, readily satisfy spine equilibrium. Hence, the solution space that is searched by the optimization search engine is much smaller than the case when a force-driven approach is implemented. Therefore, in our approach, from all possible sets of lumbar segmental kinematics that can be distributed across lumbar vertebrae and generate the total 30° lumbar flexion, we will search (i.e., through optimization procedures) for a set of lumbar segmental kinematics where the associated TNS minimizes the desired cost function. Such a methodological choice (i.e., kinematics- versus force-driven), however, does not affect the outcomes. In the following subsections, we first elaborate on the kinematics-driven approach for the estimation of TNS and subsequently present the structure of the optimization algorithm.

1. Estimating trunk neuromuscular strategy using the kinematics-driven approach

A nonlinear finite element (FE) model of spine, developed in the ABAQUS software (Version 6.13, Dassault Systémes Simulia, Providence, RI), is used in the kinematics-driven approach to estimate the moment at each lumbar vertebra to be balanced by muscles attached to that same vertebra (Arjmand et al., 2009; Bazrgari et al., 2007).

In the FE model of spine, the thoracic region and lumbar spine vertebrae are simulated by rigid elements and intervertebral discs are simulated by nonlinear flexible beam elements (Fig. 1). Inputs to the FE model include sagittal plane rotational boundary conditions at the T12 to S1 spinal levels along with the ~50% of total body weight distributed across the entire spine (Arjmand and Shirazi-Adl, 2006b). A muscle architecture including 56 muscles attached to the spine from lumbar and thorax to pelvis is considered for estimation of TNS required to balance moments at lumbar vertebrae. Since the attached muscles to each level (i.e., 10 muscles in each level from T12 to L4 and 6 muscles in the level L5) outnumbers the moment equilibrium equations, a local[1] optimization procedure is used to estimate muscle forces at each level as follows:

$$\begin{cases} \text{Var } \boldsymbol{F} \\ Cost\ function = g(\boldsymbol{F}) \\ \text{Minimize } (cost\ function) \\ \text{Subject to} \displaystyle\sum_{i=1}^{m} r_i \times F_i = M \end{cases} \tag{1}$$

where F_i and r_i denote the force and the moment arm of the i^{th} muscle, respectively and m is the number of muscles attached to that level and M is the output (reaction) moment. Depending on the assumed TNS, the cost function $g(\boldsymbol{F})$ was considered to be sum of squared muscle stresses, sum of squared muscle forces, passive moment, compression, and shearing force at the L5-S1 intervertebral disc. A classic optimization technique (i.e., Lagrange Multiplier Method) is used to solve the local optimizations. Given the nonlinearity of FE model, the impact of estimated muscle forces on mechanical response of the model is also considered by application of the estimated muscle forces to the model as external loads and accounting for any residual moment estimated at each lumbar level in calculation of muscle forces. Such iterative procedure is stopped when the residual moments estimated at each lumbar level become negligible (i.e., < 0.1 Nm).

[1] The local optimization was used to estimate muscle forces and is different from the main optimization algorithm introduced in the next subsection.

Fig. 1 may be inserted here

2. Finding the lumbar segmental kinematics that is associated with a desired neuromuscular strategy

An optimization procedure (hereafter called global optimization), that implements a heuristic genetic algorithm to find the lumbar segmental kinematics associated with a desired TNS, was developed (Shojaei et al., 2015). The genetic algorithm involves 100 generations and 30 individuals in each generation (i.e., a total number of 3000 individuals/iterations), and the stop criterion is considered as the tolerance of 10^{-3} for both variables (i.e., segmental kinematics and cost function). For each set of generated lumbar segmental kinematics (e.g., the kinematics for i^{th} individual in the j^{th} generation) by the algorithm, TNS is estimated using the method described in the previous section and is used to calculate the cost function of optimization (see Eq. 2). The optimization procedure was formulated as:

$$\begin{cases} \text{Var } \boldsymbol{\theta} = \left[\theta_{L_1}\theta_{L_2}\theta_{L_3}\theta_{L_4}\theta_{L_5}\right] \\ Cost\ functin = g(\boldsymbol{F})\left(1+\alpha\sum_{i=1}^{n=62} max[0,k]\right) \\ \text{Minimize } (cost\ function) \\ \\ \text{Subject to} \\ 0 \leq F_i \leq \sigma_{max} \times PCSA_i \\ -9.6^{\circ} \leq \theta_{T_{12}} - \theta_{L_1} \leq 6^{\circ} \\ -9.6^{\circ} \leq \theta_{L_1} - \theta_{L_2} \leq 6^{\circ} \\ -12^{\circ} \leq \theta_{L_2} - \theta_{L_3} \leq 3.6^{\circ} \\ -14.4^{\circ} \leq \theta_{L_3} - \theta_{L_4} \leq 1.2^{\circ} \\ -15.6^{\circ} \leq \theta_{L_4} - \theta_{L_5} \leq 2.4^{\circ} \\ -10.8^{\circ} \leq \theta_{L_5} - \theta_{S_1} \leq 6^{\circ} \end{cases} \tag{2}$$

where θ_{L1} to θ_{L5} are vertebral kinematics from L1 to the L5 respectively and are generated by global optimization procedure. n = 62 denotes the number of optimization constraints including 56 constraints for muscle forces and 6 rotational constraints. F_i and $PCSA_i$ denote the force and the physiological cross section area of i^{th} trunk muscle respectively, k is the number of estimated muscle forces that exceed the muscle force boundaries plus the number of violated rotational constraints, α is a penalizing value, and σ_{max} is the maximum allowable stress in the muscle (i.e., assumed to be 1.0 MPa). θ_{T12} and θ_{S1} are inputs of the global optimization representing the rotation of the T12 and the S1 vertebrae. The rotational inequality constraints denote modified sagittal plane range of motion of lumbar motion segments with negative sign denoting flexion. These were obtained by adding a 20% increase to the mean reported values in Adams et al., (2013) to account for individuals' variability.

The flowchart of the procedure for finding the lumbar segmental kinematics that is associated with a desired TNS is presented in Fig. 2.

Fig. 2 may be inserted here

Results

The estimated angular and translational deformations of lumbar motion segments in the sagittal plan under the five TNSs studied here are presented in the Table 1. Minimum changes in the angular and translational deformations of a motion segment with alterations in TNS ranged from 0° (L2-L3 segment) to 0.5° (L4-L5 segment) and 0 mm (L1-L2 and L2-L3) to 0.04 mm (L4-L5), respectively (Table 1). Similarly, maximum changes in the angular and translational deformations of a motion segment with alterations in TNS ranged from 2.4° (L2-L3 segment) to 7.5° (L5-S1 segment) and 0.11 mm (L2-L3) to 0.39 mm (L3-L4), respectively (Table 1). For each TNS, the values of all five cost functions used to estimate different neuromuscular strategies are summarized in Table 2. As expected, the minimum value of a cost function was associated with the TNS estimated to minimize that cost function.

Table 1 may be inserted here

Table 2 may be inserted here

Discussion

Estimation of lumbar segmental kinematics for neuromuscular strategies that optimize specific aspects of lower back biomechanics was conducted using a finite element musculoskeletal model of the spine within an optimization procedure, and the changes in lumbar segmental kinematics due to alterations in TNS were determined. The differences in kinematics of at least five (out of twelve: i.e., six angular and six translational deformations) cases between each two neuromuscular strategies appears to be detectable by current imaging techniques (e.g., computed tomography, magnetic resonance) whose precision have been reported to be ~ 0.1 mm and ~ 0.1° (Iwata et al., 2013; Keller et al., 2003; Ochia et al., 2006; Shymon et al., 2014). Particularly, the differences in kinematics of lumbar segments between each combination of two TNSs (10 possible combinations) are detectable in 97% of cases for angular deformation and 55% of cases for translational deformation. Therefore, combined imaging and computational modeling appears to have potentials for predicting alterations in TNS.

While image-based information have been used for development of subject-specific mechanical models of spine (Diamant et al., 2005; Eskandari et al., 2017; Fagan et al., 2002; Ghezelbash et al., 2016; Lafon et al., 2010; O'Reilly and Whyne, 2008; Petit et al., 2004; Shymon et al., 2014), previous studies have primarily used image-based information to personalize geometry (e.g., vertebra/disc dimensions, muscles cross-sectional areas and insertion points) and/or mechanical property of spine models (Diamant et al., 2005; Eskandari et al., 2017; Fagan et al., 2002; Ghezelbash et al., 2016; Lafon et al., 2010; O'Reilly and Whyne, 2008; Petit et al., 2004). Furthermore, some of these studies have been conducted in tissue level (Diamant et al., 2005; Fagan et al., 2002), have been designed for specific group of patients (Lafon et al., 2010; Petit et al., 2004), and oversimplified the spine model by disregarding the effects of muscle forces when calibrating using experimental measures (Lafon et al., 2010; Petit et al., 2004). To the best of our knowledge, the current study is the first effort toward personalized assessment of trunk neuromuscular behavior through geometrical information from imaging combined with optimization-based modeling.

The value of each cost function when calculated using its associated deformations of lumbar motion segments (i.e., the diagonal in Table 2) was, as expected, the minimum value in each column of Table 2. However, what is notable in results presented in Table 2 is that an abnormal TNS could result in loads and/or deformations in some areas of lower back that are larger than what is normally resisted by those areas. For instance, a hypothetical TNS that minimizes shearing force at the L5-S1 intervertebral disc resulted in an increase of ~ 350N in compression force when compared to a strategy that was considered normal in this study (i.e., the strategy that minimizes sum of squared muscle stresses). Similarly, a strategy that minimizes compression force or muscle forces, compared to the normal strategy, led to large muscle stresses. Although the short term effect of a specific TNS can be beneficial, for instance by protecting the injured tissues, the long term consequences of altered TNS could be an injury to other lumbar tissues due to compensatory resisted larger than normal loads (Hodges and Smeets, 2015). Therefore, prediction of any abnormality in trunk neuromuscular control of spinal equilibrium and stability using the proposed imaged-based method may offer a platform for better control and management of LBP.

In the present study, we postulate that TNSs optimize some aspects of lower back biomechanics. Though alterations in TNS have been reported in the literature, our assumption might not be accurate and were merely made for the purpose of this feasibility study. Furthermore, in all cases, the abnormal TNS that minimizes loads in a tissue was represented by a single-force cost function which was a simplified assumption. For example, minimizing the loads on the facet joint involves reducing both shearing and compression forces, though shearing is the dominant force in characterizing facet join environment. In conclusion, results of this feasibility study, support the idea of image-based assessment of TNS using computational models. Specifically, a geometrically and materially subject-specified model of the spine can be used in future to obtain the neuromuscular strategy that generates the closest lumbar kinematics to those measured from imaging. The accuracy of such assessment strategy can further be improved by implementing dynamic rather than static assessment tasks.

Acknowledgements

This work was supported, in part, by an award (5R03HD086512-02) from the National Center for Medical Rehabilitation Research (NIH-NICHD) and the Office of the Assistant Secretary of Defense for Health Affairs, through the Peer Reviewed Orthopaedic Research Program (award #W81XWH-14-2-0144).

Conflict of interest statement

We declare that all authors have no financial or personal relationships with other persons or organizations that might inappropriately influence our work presented therein.

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TABLE AND FIGURE CAPTIONS

Table 1: The estimated angular (°) and translational (mm) deformations of lumbar motion segments in the sagittal plane under TNSs that minimize 1) sum of squared muscle stresses, 2) sum of squared muscles forces, 3) L5-S1 compression force, 4) L5-S1 anterior-posterior shearing force, and 5) L5-S1 passive moment.

Table 2: The value of cost functions (horizontal top) under the five neuromuscular strategies (vertical left) studied here.

Figure 1: A schematic model of the spine and its components (left), the musculatures in the sagittal (right) and frontal (middle) planes in upright posture. ICpl: iliocostalislumborum pars lumborum, ICpt: iliocostalislumbroum pars thoracis, IP: iliopsoas, LGpl: longissimusthoracis pars lumborum, LGpt: longissimusthoracis pars thoracis, MF: multifidus, QL: quadratuslumborum, IO: internal oblique, EO: external oblique and RA: rectus abdominus.

Figure 2: The algorithm used for finding a set of lumbar segmental kinematics that its associated neuromuscular strategy minimizes a cost function

Table 1: The estimated angular (°) and translational (mm) deformations of lumbar motion segments in the sagittal plane under TNSs that minimize 1) sum of squared muscle stresses, 2) sum of squared muscles forces, 3) L5-S1 compression force, 4) L5-S1 anterior-posterior shearing force, and 5) L5-S1 passive moment.

	Angular deformations						*translational deformations*					
	T12-L1	L1-2	L2-3	L3-4	L4-5	L5-S1	T12-L1	L1-L2	L2-L3	L3-L4	L4-L5	L5-S1
$\sum Stress^2$	3.0	5.1	4.8	3.6	5.7	7.5	0.70	1.10	1.22	1.24	1.48	0.75
$\sum Force^2$	7.8	7.5	4.8	1.5	2.4	5.7	0.97	1.19	1.22	1.09	1.20	0.70
Compression force	7.9	6.8	6.0	2.1	1.9	5.6	0.97	1.10	1.24	1.07	1.15	0.69
Shearing force	5.7	3.3	5.1	7.5	7.8	0.9	0.89	0.96	1.21	1.37	1.52	0.81
L5-S1 passive moment	4.2	6.6	7.2	7.8	4.2	0.0	0.87	1.18	1.32	1.46	1.44	0.86
Minimum change	0.1	0.2	0.0	0.3	0.5	0.1	0.02	0.0	0.0	0.02	0.04	0.01
Maximum change	4.9	4.2	2.4	6.3	5.9	7.5	0.27	0.23	0.11	0.39	0.37	0.17

Minimum and maximum change in each column were, respectively, the smallest and largest value of difference between the deformations of any two TNS.

Table 2: The value of cost functions (horizontal top) under the five neuromuscular strategies (vertical left) studied here.

	$\sum Stress^2$	$\sum Force^2$	Compression force (N)	Shearing force (N)	L5-S1 passive moment (Nm)
$\sum Stress^2$	8.39e+11	1.53e+05	1.49e+03	622.9	16.0
$\sum Force^2$	2.28e+12	6.37e+04	1.34e+03	626.2	12.1
Compression force	3.02e+12	7.02e+04	1.32e+03	601.8	12.1
Shearing force	7.10e+12	1.73e+05	1.84e+03	518.0	2.7
L5-S1 passive moment	2.86e+12	1.92e+5	1.78e+03	610.5	0.0