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Artificial neural networks to predict 3D spinal posture in reaching and lifting activities; Applications in biomechanical models

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ABSTRACT

Spinal posture is a crucial input in biomechanical models and an essential factor in ergonomics investigations to evaluate risk of low back injury. In vivo measurement of spinal posture through the common motion capture techniques is limited to equipped laboratories and thus impractical for workplace applications. Posture prediction models are therefore considered indispensable tools. This study aims to investigate the capability of artificial neural networks (ANNs) in predicting the three-dimensional posture of the spine (S1, T12 and T1 orientations) in various activities. Two ANNs were trained and tested using measurements from spinal postures of 40 male subjects by an inertial tracking device in various static reaching and lifting (of 5 kg) activities. Inputs of each ANN were position of the hand load and body height, while outputs were rotations of the three foregoing segments relative to their initial orientation in the neutral upright posture. Effect of posture prediction errors on the estimated spinal loads in symmetric reaching activities was also investigated using a biomechanical model. Results indicated that both trained ANNs could generate outputs (three-dimensional orientations of the segments) from novel sets of inputs that were not included in the training processes (root-mean-squared-error ($RMSE$) $< 11°$ and coefficient-of-determination (R^2) > 0.95). A graphic user interface was designed and made available to facilitate use of the ANNs. The difference between the mean of each measured angle in a reaching task and the corresponding angle in a lifting task remained smaller than 8°. Spinal loads estimated by the biomechanical model based on the predicted postures were on average different by $< 12\%$ from those estimated based on the exact measured postures ($RMSE = 173$ and 35 N for the L5-S1 compression and shear loads, respectively).

1. Introduction

Manual material handling (MMH) activities are identified as risk factors for low back pain (LBP) (Manchikanti, 2000; Thiese et al., 2014; Van Nieuwenhuyse et al., 2004). Based on the premise that excessive loads on the spine could cause injury, various biomechanical models (e.g., Arjmand and Shirazi-Adl, 2006; Cholewicki and McGill, 1996; Granata and Wilson, 2001; Stokes and Gardner-Morse, 1995), lifting analysis tools (Potvin, 1997; McGill, 1997; Arjmand et al., 2011, 2012, and 2013), and commercial software such as the University of Michigan's 3D Static Strength Prediction Program™ (3DSSPP) (University of Michigan Center for Ergonomics, 2014) and Anybody Modeling System™ (AnyBody Technology, Aalborg, Denmark) (Damsgaard et al., 2006) have been developed to estimate spinal loads in MMH activities.

In order to estimate muscle forces and spinal loads during MMH activities, biomechanical models need hand-load and posture characteristics as input. While load variables, i.e., mass of the handled load and its position are easy to estimate based on simple measurement devices (e.g., bathroom scale and tape measure), posture variables including three-dimensional orientations of the pelvis, lumbar, and thorax are usually evaluated using skin-mounted motion capture devices such as optical motion capture systems, electromagnetic, and inertial tracking systems (Arjmand and Shirazi-Adl, 2006; Arjmand et al., 2009, 2010; Cholewicki and McGill, 1996; Hajibozorgi and Arjmand, 2016; Marras et al., 1992). Motion capture techniques are, however, limited to equipped laboratories and thus impractical for easy use in workplaces for ergonomics or biomechanics applications. Biomechanical modeling studies that aim to estimate spinal loads currently need an inevitable parallel time-consuming in vivo study to measure spinal posture during activities under consideration.

As an alternative to measurements, posture prediction models based on the inverse-kinematics approach and a body link-segment

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model (a linkage structure modeling the human body with several links (bones) whose end points represents body joints) have been developed to calculate the body posture for a given hand and foot position (e.g., Dysart and Woldstad, 1996; Marler et al., 2011; Woldstad, 1997). These links usually represent forearms, upper arms, torso, thighs, and shanks. The linkage model representing different body segments is kinematically a redundant system. That is, there exists many different possible postures (link orientations) for a given hand and foot position. An optimization approach should therefore be used to predict a mathematically feasible and optimal posture. Various optimization algorithms, such as minimizing joint torques or maximizing body stability (balance), have been employed to predict body link orientations (posture) (Dysart and Woldstad, 1996). These models, however, may predict postures that are indeed very different from the actual postures adapted by individuals.

Regression equations (Beck, 1992; University of Michigan Center for Ergonomics, 2014) and artificial neural networks (ANN) (Perez and Nussbaum, 2008) developed based on human body posture measured in vivo (motion capture data) have been used to predict whole body posture. Errors between measured (actual) and predicted posture are usually large in these models (on average 20° for joint angles) with some of the errors being considerable (~41°) particularly for 3D conditions. Such large errors can, at least partly, be due to the inherent large inter-individual variabilities in the adapted posture for a given load position, and may in turn discourage investigations that aim to develop subject-specific posture prediction models. Incorporating a lot of anthropometric data as input of and many joint angles (whole body posture) as output of an ANN (Perez and Nussbaum, 2008) could be other sources of the low to moderate predictive quality of such ANNs. For the evaluation of risk of injury to the spine, however, outputs of such ANNs can be reduced to the spinal posture (rather than the whole body posture) so to improve their predictive power.

The objective of the present study is therefore twofold:

1. To investigate the capability of the ANNs in predicting 3D spinal posture (S1, T12 and T1 orientations) in various reaching and lifting activities. Two ANNs are trained and tested using spinal postures measured by an inertial tracking device during these activities. Inputs of each ANN is the position of the hand load and body height (as the most important personal-related variable in determining posture) while its outputs are nine Eulerian rotations of the three foregoing segments. It is hypothesized that such population-based ANNs will be robust tools in predicting spinal posture during 3D reaching and lifting activities.
2. To estimate compressive and shear spinal loads in various symmetric load reaching activities using our biomechanical model (Arjmand et al., 2011) and based on the posture predicted by the ANNs and to compare these loads with those estimated based on the exact posture measured by an optical motion capture system. Application of the ANNs in biomechanical models is shown and the effect of posture prediction errors on these loads is investigated.

2. Materials and methods

2.1. Inertial tracking device

Three small (38 mm × 53 mm × 21 mm) inertial and magnetic sensors (Xsens MTx, Xsens Technologies, Enschede, Netherlands) were used to capture the 3D rotations of the pelvis (S1), T12 and thorax (T1). Each sensor has triaxial accelerometers, gyroscopes, and magnetometers whose signals are fused using a built-in Kalman filter (XKF3) to estimate optimal drift-free 3D orientations of the sensor coordinate system. Measurements of gravity (by the 3D accelerometers) and the earth magnetic north (by the 3D magnetometers) are used to eliminate any drift of the gyroscopes using the Kalman filter (Xsens Technologies, 2010). A reference earth-fixed coordinate system is also created using information from the inertial and magnetic sensors. Before starting the trials accuracy of the inertial sensors was assessed by measuring the angles between two (fixed and movable) arms of a goniometer as described elsewhere (Tafazzol et al., 2014). The error (difference between the known angle of the goniometer arms and the measured angle by the inertial sensors) was found to be less than 0.6° indicating that the device can be used for accurate measurements of the spine kinematics (Hajibozorgi and Arjmand, 2016; Tafazzol et al., 2014).

Table 1
Body height, body weight, age, and body mass index (BMI) of volunteers participating in the study (mean (standard deviation)).

	Body height (cm)	Body weight (kg)	Age (year)	BMI (kg/m^2)
All subjects, 40 males	178.2 (5.2)	74.6 (10.8)	24.2 (1.2)	23.5 (3.0)
Group 1 (reaching), 20 males	179.7 (5.9)	75.5 (11.1)	24.1 (1.2)	23.4 (3.1)
Group 2 (lifting), 20 males	176.4 (3.8)	73.5 (10.8)	24.3 (1.2)	23.6 (3.0)

2.2. Subjects and protocol

Forty healthy young male individuals with no history of back surgery or recent back, hip or knee pain volunteered for the study after signing an informed consent form (Table 1). Inertial sensors were securely attached to the overlying skin of the S1, T12, and T1 spinous processes using double-sided tape (Fig. 1a).

2.3. Reaching and lifting activities

Subjects were divided into two matched (body height, weight, age, and BMI, $p > 0.05$) groups (Table 1). One group performed reaching activities (only reaching a load of 5 kg) while the other group performed load-handling activities (i.e., static lifting of 5 kg). Each subject performed 45 tasks by reaching or lifting a 5 kg weight located at 9 different anterior-right positions (x and y) (Fig. 1b) and at 5 different heights (i.e., z=0, 30, 60, 90, and 120 cm from the floor). Subjects were instructed to avoid pivoting their feet during the tasks and kept their target posture for 3 s. They were, however, free to adapt a stoop or squat technique or to bend from the pelvis or lumber (lordotic or kyphotic technique). In other words, in this study we aim to predict the posture that subjects freely choose to perform a given activity.

2.4. Data analysis

As described elsewhere (Hajibozorgi and Arjmand, 2016; Tafazzol et al., 2014), the device measures real-time 3D orientation of the sensors coordinate systems with respect to a global fixed coordinate system (${}^{S}_{G}R$). As the orientation of the sensor unit coordinate system (S) is not necessarily aligned with that assumed for the body segment (B), a body segment to sensor orientation matrix (${}^{B}_{S}R$) needs to be defined. Orientation of a body segment frame (B) (i.e., T1, T12, and S1) with respect to the global earth-fixed frame (G) was thus computed as:

$$ {}^{B}_{G}R = {}^{S}_{G}R\,{}^{B}_{S}R \tag{1}$$

Relative rotation of each body segment to the initial upright posture (${}_{G}{}^{B}R|_{r}$) can be computed as:

$$ {}^{B}_{G}R\Big|_{r} = {}^{B}_{G}R\,{}^{B}_{G}R^{-1}{}_{t=0} \tag{2}$$

where ${}_{G}{}^{B}R_{t=0}$ is the unknown orientation of the body segment with respect to the global coordinate system. Subsequently, and to eliminate this unknown matrix one can write:

$$ {}^{B}_{G}R\Big|_{r} = \left({}^{S}_{G}R\,{}^{B}_{S}R\right)\left({}^{B}_{S}R^{-1}{}_{t=0}\,{}^{S}_{G}R^{-1}{}_{t=0}\right) \tag{3}$$

It is assumed that there is no movement between the sensors and underlying skin (sensors are attached firmly to the skin):

$$ {}^{B}_{S}R\,{}^{B}_{S}R^{-1}{}_{t=0} = I \tag{4}$$

where I is the unit (identity) matrix. Relative rotation of each body segment (i.e., T1, T12, and S1) to the initial upright posture (${}^{B}_{G}R|_{r}$) as the subject reached or lifted the load was described using a rotation matrix as:

$$ {}^{B}_{G}R\Big|_{r} = {}^{S}_{G}R\,{}^{S}_{G}R^{-1}{}_{t=0} \tag{5}$$