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Spinal Moment Contribution of Load Handling Estimated from Back Extensor EMG Applying Artificial Neural Network Technology

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INTRODUCTION

A methodology was proposed for practical ambulatory assessment of low back load exposure [11, approaching the accuracy of 'golden standard' elaborate laboratory methods. It uses 2 small inertial sensor modules assessing absolute posture and movement of trunk and pelvis, 2 or more EMG sensor modules recording trunk muscle EMG and a portable data acquisition system. Output load exposure parameters include kinematic parameters of trunk and pelvis, trunk muscle EMG patterns and spinal moment estimations around a single rotation center in the intervertebral body at level L5/S1 .
The spinal moment is estimated in 2 separate components. First there is the contribution of weight and inertia of the trunk and head estimated from trunk kinematics alone. A second component is the contribution of weight and inertia of arms and load handled or external force present. A key role is played here by a self-learning calibration system predicting this component from back extensor EMG signals and trunk kinematic data.
This paper discusses validation of the estimation method of the second component against a 'golden standard' reference system in lifting experiments

METHODS

The moment contribution of trunk and head is estimated using a simple two segment cantilever model presented and validated before [2]. Inputs for the model are: trunk absolute tilt, trunk angular velocity and acceleration, all in the saggital plane of the trunk, and trunk vertical acceleration and 4 antropometric parameters describing size and weight of the subject.
The moment contribution of the arms plus load handling is estimated using EMG signals from the back extensor muscles. Considering bad occasion to occasion reproducibility a reliable estimation of spinal moment from EMG can only be given when the EMG-moment relationship is calibrated in every recording occasion covering the relevant range of postures and movement and include a representative set of muscles. A typical traditional approach would include an elaborate set of separate recordings of moment and EMG from several muscles under many combinations of posture, movement and external load. This is not acceptable for ambulatory assessment.
An alternative, potentially more practical method for this calibration applies artificial neural network technology in creating a self-learning calibration system that only needs a small set of random postures and movements data with different external loads.
The back propagation type neural network is trained in supervised mode using as inputs Smoothed Rectified EMG signals derived from 4 positions on the erector spinae musculature. These positions are 3 cm left and right from the spine at level TlO and L2. To enable the calibration system to include modulation of muscle length and contraction velocity trunk and pelvic absolute tilt, trunk angular velocity (and trunk angular acceleration) are offered as inputs. The network only output is the back extension moment. The back propagation network has 1 hidden layer with 5 levels.
A training set was derived from 4 recordings of 20 seconds where a subject was asked to perform back flexion and extension movements with increasing or decreasing swiftness and with or without a stop in the middle of the movement. This was done with 2 different weights (0 and 15.7 kg) held in a standardized, exactly known and steady fashion. This enabled direct estimation of the moment contribution using kinematics of arms and load. These estimations were offered together with the input signals to the artificial neural network under training as desired outputs, thus enabling supervised learning.

Selection of learning moments from the data was guided by the desire for a uniform distribution of the spinal moment. The calibration was regarded valid as long as EMG electrodes and movement sensors would stay in the same place and orientation.
The method was validated by direct comparison of spinal moments against a ‘golden standard’ reference method using a ground reaction force recording from a force plate, lower extremities and hip kinematics determined using a video based movement analysis system (Vicon) and a linked segment model of the lower extremities [3]. Validation included single lifts with different lifting techniques (symmetric leg, back and free lifts plus asymmetric free lifts) at different lifting speed (slow and fast) and with different loads (6.7 kg and 15.7 kg).

RESULTS

Fig. 1 shows 2 typical results for lifting experiments from the same subject (single slow leg lift with load of 15,7 kg and free asymmetrical lift of 30 degrees out of the saggital plane with 6.7 kg). The upper trace shows the load handling contribution to the spinal moment predicted by the calibration system (‘load predicted’) and directly calculated by the algorithm used for estimation desired output values in the learning phase (‘load model’). The second plot shows total spinal moment estimated by the reference system (‘ref), the moment contribution of the trunk and head alone (‘trunk’) and the sum of the both trunk and head component and load handling component (‘trunk + load’). Experimental conditions allowed only valid estimation of the load component after load lift off (vertical line).

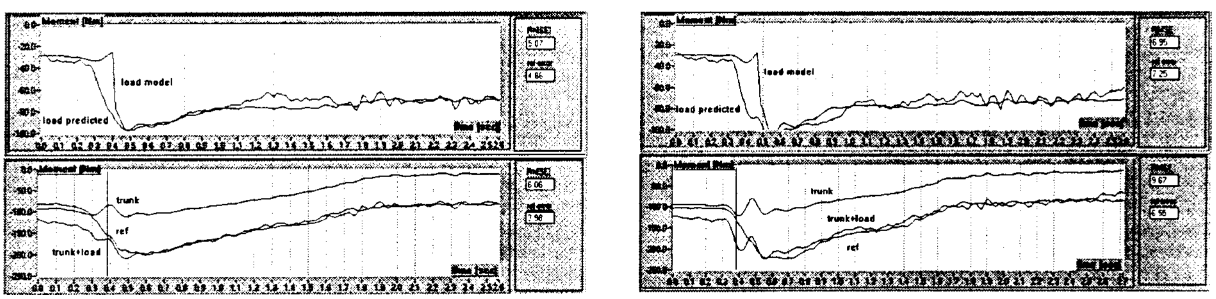

Fig I: Estimated moment curves for leg lift (left) and free asymmetric lift at 30 degree (right). Upper trace: predicted and trained data from the calibration system. Lower trace: Predicted trunk (‘trunk ') and total trunk + load hanclling components (‘trunk + load’) against reference estimation of total spinal moment (‘ ref').

The estimation of total spinal moment stayed for all lifting techniques well within 10% average relative error. Both trunk and load component contributed significantly.
By feeding only one or part of the input signals as input to the calibration system it was determined that the artificial neural network used mainly the EMG signals for estimating the moment contribution of load handling. Using any combination of the kinematic parameters gave a poor estimation of the load handling contribution over the whole lifting trial. Adding kinematic parameter inputs to the EMG inputs gave a systematic but small improvement.
Typical errors in overall moment estimation were similar over all trials with one person but differed over persons, with the largest error in a rather small subject. This indicates that this was probably caused by inaccuracy in the antropometric parameters.