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PREDICTING THE LUMBAR MOMENT FROM TRUNK KINEMATICS AND ELECTROMYOGRAPHY : MULTIPLE LINEAR REGRESSION OR ARTIFICIAL NEURAL NETWORK?

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SUMMARY

Multiple linear regression and artificial neural network were used to predict the lumbar moment during asymmetrical manual handling based only on trunk kinematics and surface electromyography of six muscles. Lumbar moments were previously estimated using a validated linked-segment model. Four trials were used to calibrate the variables to the lumbar moment, and the validation was made on another set of 28 trials. The results show that both methods have good predictive capacity and could be used for field assessments.

INTRODUCTION

Low back disorders (LBD) related to manual materials handling (MMH) remains an important health issue. The underlying biomechanical assumption is that injury occurs when the load imposed upon a tissue exceeds the tolerance of that tissue [1]. Biomechanical studies also suggest that cumulative load exposure metrics may provide a promising measure of LBD risk [2]. There is a need to develop methods and instrumentation that can accurately quantify the L5/S1 joint moment encountered in real work settings. Previous work has shown that ambulatory assessment of 3D trunk kinematics is feasible [3]. The purpose of the present paper is to explore whether combining trunk muscle electromyography (EMG) and trunk kinematics could predict the L5/S1 joint moment in asymmetrical MMH. Two methods to calibrate the EMG and kinematics to the resultant lumbar moment were contrasted: multiple regression and artificial neural network.

METHODS

Thirty subjects (mean age 31.6 (SD 10.4) years, body mass 75 (SD 11.6) kg, height 1.73 m (SD 0.06)) participated to the study. They had to transfer four boxes (one of 23 kg and three of 15 kg) of identical size (26 cm depth x 34 cm width x 32 cm height) from a conveyor to a trolley separated by 1.5 m, and back to the conveyor. One trial consisted in the transfer of four boxes (either to or from the trolley), and each subject performed 32 trials for a total of 128 lifts.

An optoelectronic system was used to determine whole body kinematics, ground reaction forces were measured using a large force-plate, and EMG signals of ten trunk muscles (longissimus, iliocostalis, external and internal oblique, multifidus, bilaterally) were measured. A validated dynamic 3D linked-segment model was used to estimate the resultant moment at L5/S1 [4]. These lumbar moments served as the criterion measure.

Trunk kinematics and EMG were used to predict the lumbar moment. Variables that were correlated with the resultant lumbar moment were selected and some variables that were inter-correlated or posed technical difficulties were eliminated. The linear envelope of six muscles (longissimus, iliocostalis and external oblique, bilaterally) were selected. The trunk to pelvis flexion angle and angular acceleration, the trunk inclination with respect to the vertical, and the linear acceleration of the sacrum were the kinematic variables included. These kinematics variables can easily be measured using an ambulatory hybrid system [3] as well as EMG signals.

Two approaches, multiple linear regression (MLR) and artificial neural network (ANN), were used to calibrate the EMG and trunk kinematics to the lumbar moments on a subject by subject basis, using the same kinematics and EMG variables. Four of the 32 trials were used for calibration (calibration data set), two towards the trolley and two towards the conveyor. The cross-validation was performed on the other 28 trials (validation data set). For each subject's calibration data set, standard MLR (minimizing the sum of squared differences between predicted and observed resultant lumbar moments) was used to determine the regression coefficients and a three-layer feed-forward ANN model (two hidden nodes, tangential-sigmoid activation function; back-propagation training algorithm) was trained. The predicting performance of both methods was assessed with the validation data set.

The coefficient of determination (R^2), the root mean square error (RMSE), and the RMSE over the peak lumbar moment (RMSE/PM) as a relative error, as well as the error on peak loadings expressed by the ratio of the peak criterion moment over the peak predicted moment (PM/PMp) were used to assess the predicting performance of the two models'.

RESULTS AND DISCUSSION

The two approaches predicted the resultant lumbar moment of the validation data set with a mean explained variance (R^2) of 77%, a mean RMSE of 25 N·m and a relative error (RMSE/PM) below 10% (Table 1). Both approaches were also able to predict peak lumbar moments on average within 5%, although larger variability was observed for this performance index (Table 1). The difficulty of predicting instantaneous peak lumbar moments can also be appreciated in Figure 1, which shows a typical example of the criterion and predicted resultant lumbar moment curve for one trial of a subject.

Table 1. Coefficient of determination (R^2), root mean square error (RMSE), relative error (RMSE/PM) and error on peak values (PM/PMp) for the prediction of the resultant lumbar moment using the multiple linear regression (MLR) and the artificial neural network (ANN) models for the calibration and validation data sets. Mean over all subjects (ranges).

Model	R^2	RMSE (N·m)	RMSE/PM (%)	PM/PMp (%)
Calibration set				
MLR	0.78 (0.67, 0.85)	24.5 (17.4, 35.1)	9.0 (7.0, 11.0)	93.5 (73.7, 123.5)
ANN	0.86 (0.76, 0.91)	19.5 (14.4, 28.5)	6.5 (4.8, 8.8)	102.2 (84.9, 127.6)
Validation set				
MLR	0.74 (0.53, 0.83)	26.7 (19.8, 38.1)	9.0 (8.0, 12.0)	105.3 (78.5, 165.4)
ANN	0.80 (0.51, 0.89)	24.0 (15.8, 34.3)	8.0 (6.5, 10.4)	104.0 (82.8, 140.0)

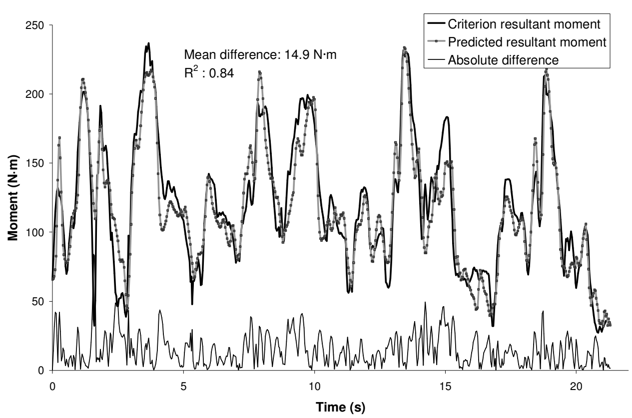

Figure 1: Typical example of the criterion and predicted resultant lumbar moment by the artificial neural network model.

The results of this feasibility study showed that good predictions of the resultant lumbar moment during asymmetrical MMH can be obtained by capturing a limited number of trunk kinematics and EMG signals. The calibration of these variables to the lumbar moment should be performed using similar MMH tasks as the ones under study. Although such a calibration represents a challenge for field application, simplified approaches could be used and eventually allow individual calibration. Only four trials were needed for calibration, which included two box weight, four lifting height as well as the lifting and lowering of the boxes, to predict the moment of 28 other trials. Such a small amount of data for calibration is an interesting feature for field application of the method.

The fact that a small performance difference was observed between the MLR and the ANN models reveals that the non-linearity of the relation between the lumbar moment and the kinematics and EMG variables plays a minor role, and that both methods could be used with success.

CONCLUSIONS

Predicting the lumbar resultant moment during asymmetrical MMH from trunk kinematics and muscle activation variables can be successfully realized either by MLR or ANN. Of course, the calibration data set included similar MMH tasks as the one under study. If such a calibration is feasible (next development step), the lumbar moments could be assessed continuously using the described models during real work tasks while the subject is wearing ambulatory instruments to record trunk muscle activation and kinematics.

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