Inertial Sensor-based Measurement of Thoracic-Pelvic Coordination Predicts Hand-Load Levels in Two-handed Anterior Carry

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INTRODUCTION

Carrying heavy hand loads frequently and for long durations is a known risk factor for low back disorders. Two-handed anterior carry is a common carrying posture performed regularly at work places, but shows the largest increase in anterior-posterior shear loading compared to other carrying postures such as one-handed carry, backpack carry, and shoulder carry. A two-handed load of just 11.3 kg causes spinal shear loads to exceed the recommended exposure limits and may potentially damage spinal tissues (Rose, Mendel, & Marras, 2013).

Prediction of load levels remotely using the wearable sensors could help quantify biomechanical exposures from load carriage *in situ* particularly in jobs where the duration and magnitudes of loads carried vary across time (e.g., warehousing, and mail delivery). The mode and magnitude of load carriage produces biomechanical adaptations reflected in changes in posture and gait patterns, specifically in the movement coordination between the torso and pelvis (Lim & D'Souza, under review). The mean relative phase angles is a measure of coordination between multiple body segments during complex, multi-joint movements (Burgess-Limerick, Abernethy, & Neal, 1993).
The objective of this study was to build and validate a statistical prediction algorithm that uses measures of thoracic-pelvic coordination, namely, mean relative phase angles, computed from body-worn inertial sensor data for classifying hand-load levels in a two-handed anterior load carrying task.

METHODS

Nine males participated in a laboratory experiment carrying a hand load with both hands anteriorly positioned down a levelled corridor for a distance of 24m. The participants first performed no-load walk trials, followed by 4.5kg and 13.6kg walk trials, presented in a random order. Each load condition was performed twice consecutively. Body postural kinematics were recorded using four commercial inertial sensors (Opal, APDM Inc, Portland, OR, USA) attached to the sixth thoracic vertebra (T6), the first sacral vertebra (S1), and posterior-superior aspect of the right and left shank midway between the lateral femoral and malleolar epicondyles, respectively.

The classification developed involved 3 general steps with the outcome variable as a load level (no-load, 4.5kg, or 13.6kg) for each gait cycle. First, individual gait cycles were detected using a custom gait detection algorithm adapted from Aminian, Najafi, Büla, Leyvraz, and Robert (2002). Heel-strikes were detected from the angular velocity (rad/s) obtained by the right and left shank sensors, and consecutive right heel strikes were labeled as one gait cycle. Second, mean thoracic-pelvic relative phase angle in the transverse, sagittal, and coronal planes were calculated over each gait cycle and used as predictor variables. Relative phase angles were calculated using angular velocity (rad/s) data obtained from the torso (T6) and pelvis (S1) sensors. Third, the classification of load levels were performed using the Random forest technique (Breiman, 2001). Model performance was evaluated by hold-out cross-validation test repeated 20 times. Three measures of model performance, namely, average prediction accuracy, precision, and sensitivity were evaluated.

RESULTS

Model performance

The model correctly classified the load level in 85.2% (n = 685 of 804) of the validation trials. Table 1 summarizes the confusion matrix of the model along with the precision and sensitivity values from 20 cross-validation tests. Precision was similar in the No-load and 13.6 kg conditions at 90% and 91%, respectively, but lower in the 4.5kg condition at 74%. Sensitivity was the highest for the no-load condition at 95%, and the lowest in the 13.6kg load condition at 71%.

Variable importance

The relative importance of predictor variables in the classification model was examined by calculating the

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Gini impurity Index (Strobl, Boulesteix, Zeileis, & Hothorn, 2007). Mean thoracic-pelvic relative phase angle in coronal plane was found to be the most important predictor variable (normalized to 100%) followed by the transverse plane with a relative importance of 79.5% and lastly the sagittal plane with a relative importance of 66.3% compared to the coronal plane.

Table 1. Confusion matrix showing the classification result for load levels from each gait cycle data.

		Predicted Load Level			Total	Sensitivity
		No-load	4.5kg	13.6kg		
Actual Load	No-load	304	12	4	320	95%
	4.5kg	12	193	15	220	88%
	13.6kg	20	56	188	264	71%
Total		336	261	207	804	
Precision		90%	74%	91%		

DISCUSSION AND CONCLUSIONS

This study was performed as an initial step to explore the potential of using inertial sensor-based thoracic-pelvic coordination measures for hand-load level classification. Prediction of load levels can be used as an input to the low back compression/shear force calculation (e.g., using the 3DSSPP software; Center for Ergonomics, University of Michigan, MI, USA) combined with postural angles, which can also be obtained from the inertial sensors, to provide the information on cumulative low back compression force of the workers.

The sensitivity of the 13.6kg condition was relatively lower compared to other load conditions. This was due to the misclassification of 13.6kg condition as 4.5kg in 56 out of 264 gait cycles, and suggests that the mean thoracic-pelvic relative phase angles may not be discriminative in classifying load conditions between two loaded conditions. Including additional predictor variables (e.g., temporal parameters, body postural angles) to the algorithm may improve the sensitivity of the classification.

Segmenting a stream of sensor data can be performed by either using a fixed time window or by using an adaptive or dynamic time window. This study used the latter by segmenting the time-series inertial sensor data by gait cycle, which varies by person and task condition, and subsequently calculating the mean thoracic-pelvic relative phase angles within each gait cycle. Using a fixed time window, as is typically done in machine learning algorithms, may not capture differences in gait and may reduce model performance.

Future work will aim to expand the scope of the study by investigating additional carrying strategies, load levels, and predictor variables.

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