THE USE OF EMG FOR LOAD PREDICTION DURING MANUAL LIFTING

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ABSTRACT

It was hypothesized that muscle activation levels (MAL's) in the upper limb and trunk muscles are correlated with the magnitude of the load in the hands during a manual lifting task. An experimental study was run to examine alterations in the muscle activation patterns when lifting different loads. EMG signals from the biceps brachii, triceps brachii, anterior deltoid, thoracic erector spinae, lumbar erector spinae and the external oblique muscles were recorded. A system was developed using nonlinear modelling and EMG signal characteristics to correctly predict the load in the hands.

INTRODUCTION

Low back disorders are commonly developed with repetitive manual lifting [1]. Examination of the forces and moments that occur at the level of the L4/L5 vertebrae during manual lifting is needed to better understand joint loading and injury [2,3]. To find these forces and moments, the weight of the load being lifted must be known. In one study, wrist force has been estimated from the muscle activation levels (MAL's) of the upper arm muscles [4], however, there is no published work on predicting the weight lifted during manual lifting tasks. Thus, the purpose of this study is to develop a model to predict load lifted in the hands using kinematic and MAL data from arm and trunk muscles. EMG and position and orientation data were recorded as different loads were lifted in the hands using specific lifting postures and a model to predict the load lifted was determined. This information will be incorporated into an on-line system for detecting peak and cumulative joint loading at the lower back which is being developed as part of a larger study.

METHOD

Six adult males with no evidence of back pain were recruited for this study. The subjects read and signed an information and consent form approved by the Queen's University Research Ethics Board. Each subjects' age, height, weight, arm length and trunk height were recorded.

Surface EMG signals were recorded from the biceps brachii, triceps brachii, anterior deltoid, thoracic erector spinae (T9), lumbar erector spinae (L4) and the external oblique muscles. The signals were recorded using the Bortec® surface EMG system with a gain of 1000 on each channel. After the EMG electrodes were attached, subjects were asked to produce 3 maximum voluntary static contractions (MVC's) for each of the measured muscles, with 2 minutes rest between each effort.

After the MVC exercises were completed, single Polhemus Fastrak®, motion tracking receivers were placed on the subject's forearm, upper arm, neck and lower back using stretchy adhesive medical grade fabric to record the subject's kinematics.

The subjects were then asked to perform a series of lifting exercises. This involved lifting a box from the floor onto a shelf at waist height and then lifting the same box from the shelf back to the floor. The lifts were done using stoop, squat and freestyle postures. For each posture, the box was weighted to 5kg, 10kg, 15kg, 20kg and 25kg. Subjects also performed a lift with no weight in the hands (zero-load). For each position and weight, subjects repeated the lift-lower cycle three times; a total of 48 lift cycles were performed in an experimental session (6 weights x 3 postures x 3 trials).

Data Processing

All EMG signals were sampled at a rate of 1024Hz. Subsequent EMG signal processing was done using Matlab v7.0. The raw EMG data were band-pass filtered at 30 – 400Hz, rectified and then low pass filtered using a second order Butterworth filter at 2.7Hz to obtain the linear envelopes (LE's) [5].

Lift duration was defined as the time between when the box was lifted off the floor (or shelf) and when the box was released onto the shelf (or floor). This was determined with the aid of two switches, one on the handle and one on the bottom of the box. When the box was at rest, a constant (dc) voltage was recorded by the EMG recording system. When the subject grasped the handle of the box, this voltage dropped to a different dc level, and the dc level dropped again when the box was lifted off the surface on which it was resting. EMG LE values between the start and end of each lift were used in the subsequent analysis.

The LE's from all lifting trials were normalized to the maximum EMG activity attained during the MVC trials (MVC normalization). Mean value, peak value and area under the graph were calculated for the MVC normalized EMG LE's and non-normalized EMG LE's. The mean, peak and area of the non-normalized EMG LE's were also normalized using the mean, peak and area of the EMG LE for the no weight lift (zero-normalization condition). As well, the mean, peak and area of the no weight lift were subtracted from the mean, peak and area of the non-normalized EMG LE's (zero-minus condition).

A correlation comparison between the weight of the box and mean value, peak value and area under the graph for the MVC normalized, zero-normalized and zero-minus EMG LE's was calculated using Microsoft Excel 2002. A nonlinear model was then developed to predict weight lifted from the EMG parameters.

RESULTS

The results of the correlation analysis are shown in Table 1. Since the zero-normalized and zero minus EMG parameters exhibited higher correlations with the box weight, these values were used in the system modeling.

Table 1: Correlation Values between the EMG Parameters and Load for Squat Lift

Correlation with weight lifted	MVC Normalization	Zero-Normalization	Zero-Minus
Bicep Area	0.522	0.690	0.687
Bicep Mean	0.586	0.616	0.641
Bicep Peak	0.451	0.599	0.736
Deltoid Area	0.307	0.677	0.792
Deltoid Mean	0.368	0.795	0.855
Deltoid Peak	0.361	0.484	0.774
L4 Area	0.013	0.755	0.685
L4 Mean	0.030	0.760	0.720
L4 Peak	-0.163	0.564	0.440
Oblique Area	0.504	0.421	0.426
Oblique Mean	0.530	0.364	-0.003
Oblique Peak	0.506	0.069	0.328
T9 Area	0.413	0.332	0.535
T9 Mean	0.467	0.406	0.541
T9 Peak	0.465	0.252	0.477
Tricep Area	0.464	0.635	0.624
Tricep Mean	0.577	0.584	0.691
Tricep Peak	0.621	0.472	0.268

A nonlinear parallel cascade model [6] was developed to predict load lifted from the EMG signal parameters which were most highly correlated with load. Since the biceps, deltoid and L4 EMG parameters have higher correlations with the weight lifted than the other muscles; they were used in the development of the predictor model.

The system used can be seen in Figure 1. A model has been developed for the squat lift posture using area (x_1), peak (x_2) and mean (x_3) of the zero-normalized EMG LE recorded from the erector spinae (L4 level). This particular cascade gave the most accurate load prediction with an error of ±1kg. The model was developed using the EMG data from the six subjects. Then the model was tested by predicting the weight for each individual lifting trial. Table 2 gives the mean and standard deviation of the weights predicted for each of the six subjects.

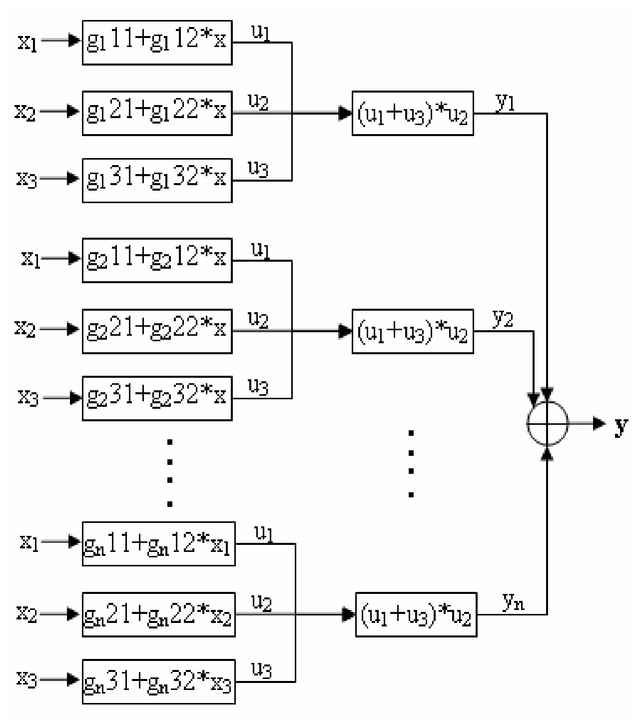

Figure 1: Parallel cascade structure for the squat lift data with n cascades: where x_1, x_2, x_3 represent the LE mean, peak and area parameters for each subject and y is the predicted weight.

Table 2: Predicted Weight Statistics

Intended Weight (kg)	Mean	Standard Deviation
5	4.9884	0.1521
10	10.0918	0.3244
15	14.9362	0.3068
20	19.9764	0.0919
25	25.0067	0.0633

DISCUSSION

Subject anthropometrics play a key role in the effects of lifting weight in the hands. For subjects who are heavier, the weight of a manual load is a smaller percentage of their total body weight and may require less energy and thus lower MAL's when lifting. However, this does not take into account the subjects' ability to lift or their overall fitness level which will also impact the effects of lifting a weight. In this study, data were normalized to minimize the anthropometric effects.

MVC exercises were completed to create a baseline to normalize the EMG. As seen in Table 1, the EMG characteristics that were processed using zero-normalization and zero-minus showed better correlation with load than values which were MVC-normalized. Producing an MVC can be uncomfortable for the subject and for accuracy purposes multiple MVC exertions are often needed. A zero weight lift is more comfortable and easy to perform in the workplace, allowing the load prediction algorithm to be more easily incorporated into real-time monitoring devices.

These preliminary results indicate that load lifted in the hands during a manual lifting task using a specific lifting posture (squat lift) can be predicted from EMG recorded from the erector spinae muscles at the L4 level. Additional models are being developed for the different lift postures – the stoop and freestyle lifts.

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