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THE USE OF THE MULTIVARIATE JOHNSON DISTRIBUTIONS TO MODEL TRUNK MUSCLE COACTIVATION

Gary A. Mirka, Naomi F. Glasscock, Paul M. Stanfield,
Jennie P. Psihogios and Joseph R. Davis

The Ergonomics Laboratory
Department of Industrial Engineering
North Carolina State University
Raleigh, North Carolina

The accurate description of trunk muscle coactivation, and more specifically antagonist muscle activity, has recently been the focus of a great deal of research in the spine biomechanics literature. The research presented in this paper is an empirical approach to the problem. Electromyographic (EMG) data were collected from 28 subjects as they performed simulated lifting tasks. These EMG data were collected from the right and left pairs of the erector spinae, latissimus dorsi, rectus abdominis, external obliques and internal obliques as subjects performed a variety of trunk extension exertions. Nine repetitions of each combination of independent variables were performed by each subject. Included in these exertions were asymmetric postures and dynamic (isokinetic and constant acceleration) exertions. The data collected during these trials were used to develop marginal distributions of trunk muscle activity as well as a 10 x 10 correlation matrix that described how the muscles cooperated in the development of these extension torques. These elements were then combined to generate multivariate distributions describing the coactivation of the trunk musculature.

INTRODUCTION

In an effort to understand the types of stresses placed on tissues of the low back during occupational lifting tasks, researchers have developed biomechanical models of the torso. Typically included in these models are ten primary muscles: erector spinae, latissimus dorsi, rectus abdominis, external obliques and internal obliques. These muscles when activated use the spine as a fulcrum to exert torques to perform useful manual materials handling tasks. One of the questions that presents itself when one is developing these biomechanical models is how to include antagonist muscle activity. Often these forces are just simply assumed to be negligible and therefore are omitted. Another concern regarding many of the existing models is that they typically take a deterministic approach to estimating muscular force, that is for a given set of circumstances (posture, load etc) the muscle activation levels are said to be constant such that equilibrium exists. Given the indeterminate nature of the biomechanical system, we should, at the very least,

consider this variability and the potential impact it may have on stresses in the low back.

An attempt to address both of these issues is found in Mirka and Marras (1993). This method involved collecting empirical muscle activity data from 5 subjects as they performed repetitive simulated lifting exertions under controlled conditions. Histograms of the muscle activity were constructed for each of the muscles under each of the conditions. These histograms were then fit to univariate Johnson distributions as described in DeBrotta et al (1989). The distributions that resulted were described by four parameters: γ (a shape parameter), δ (a shape parameter), λ (a scale parameter) and ζ (a location parameter). One of the limitations of this model was that the distributions generated were simple marginal distributions. An attempt was made to describe the coactivity of the muscles by partitioning the data space in such a way that the resulting distributions were conditional on the activity of the right and left erector spinae muscles. From a practical perspective this is limited because it ignores the potential influence that any of the other muscles might exert on any of the other

muscles. For example, might not the activity of the right latissimus dorsi affect the activity level of the left latissimus dorsi? Therefore, a much more robust approach would be to generate a 10 dimensional multivariate system that will allow each muscle to influence every other muscle. This multivariate approach is developed in this paper.

METHOD

Subjects

Twenty eight people from the university community served as subjects in this study. There were twenty one men and seven women. None of the subjects had a history of low back disorders (defined as no lost time from work or school due to back pain) and each signed an informed consent form before participating in this study. Experience in manual material handling tasks varied. Basic subject anthropometry is listed in Table 1.

Table 1. Basic Anthropometry of Subject Population

Variable	Mean	Standard Deviation
Age (years)	29.43	8.65
Body Mass (kg)	78.2	14.4
Height (cm)	175.4	8.9

Apparatus

A Kin/Com dynamometer was used in conjunction with a trunk motion reference frame to provide an environment that allowed the researchers to have a great deal of control of the forces, postures and movements of the subjects. (See Figure 1.) An EMG data processing system and a data collection system were used to gather the data describing the signals from the dynamometer (2 load cells, position potentiometer and velocity tachometer) and the muscle activity levels (ten trunk muscles). The EMG signals collected by the electrodes were amplified 1000x by miniature preamplifiers located at the muscle site. The electrode leads to the preamplifiers were kept short so as to reduce the movement noise and the external electrical noise from the surrounding environment. The signal was amplified (total amplification ~ 60,000x) and high and low pass filtered at 80 and 1000 Hz. This filtered signal was rectified and processed using a 20 msec moving average window. These processed EMG data along with torque,

angle, and velocity were collected at 100 Hz by the data collection system.

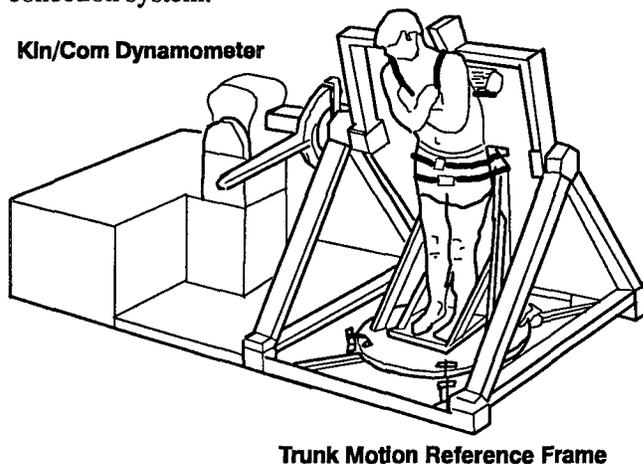


Figure 1. Experimental Apparatus (Trunk Motion Reference Frame and Kin/Com dynamometer)

Experimental Design

Independent Variables. In order to quantify the variability of the muscle forces during lifting, the subjects in this experiment were asked to perform highly controlled bending motions repeatedly. These trials included isometric, isokinetic (10 or 45 deg/sec) and constant acceleration (50 deg/sec/sec) exertions. Torque exerted by the subjects were either 30 Nm or 80 Nm for the experimental trials. (For five of the subjects the 80 Nm condition was beyond their capability and therefore the upper force level was reduced to 60 Nm for those subjects.) Two trunk positions (5 and 40 degrees of forward sagittal bend) and two levels of trunk asymmetry (0 degrees and 30 degrees twisted to the right) were evaluated in this study. Each combination of independent variables was repeated 9 times per subject. The order of presentation of the combinations of the above independent variables was completely randomized within level of asymmetry and the presentation of asymmetry was counterbalanced across subjects.

Dependent Variables. The dependent variables in this study were the normalized processed EMG values of the ten trunk muscles identified by the transverse cutting plane technique described by Schultz and Andersson (1981). These muscles included the right and left erector spinae (RES, LES), right and left latissimus dorsi (RLAT, LLAT), right and left rectus abdominis (RAB, LAB), right and left external obliques (REX, LEX) and the right and left internal obliques (RIN, LIN) muscles. The inter-electrode distance for each electrode pair was 3.0 cm.

Procedure

Upon arrival the subjects had surface electrodes applied to their skin through standard preparation procedures. The subject was then asked to enter the reference frame so that the adjustable base could be set for the subject's leg length in order to insure that the subject's L5/S1 joint was aligned with the rotating axis of the Kin/Com dynamometer. Once the subject was secured in the reference frame they performed maximum voluntary contractions (MVCs) at four positions (5 and 40 degrees of sagittal bend and 0 and 30 degrees of asymmetry). Both maximum static extensions and flexions were collected as well as the resting values in each of these postures. After these maximal exertions, the experiment began with the subject performing a sequence of randomized trials. Each of these trials dictated that the subjects perform a controlled exertion defined by set levels of torque, posture, angular trunk velocity, and angular trunk acceleration. During these trials the angular position, velocity and acceleration were controlled by the dynamometer. The exerted torque was controlled by the subject within a tolerance of +/- 10% using a graphical video feedback system that displayed their instantaneous torque output as well as the target torque designated for the particular trial. If the subject failed to maintain the designated amount of torque the trial was repeated.

Data Analysis

The EMG data were first normalized with respect to the maximum and resting EMG values that occurred at each particular trunk posture. The main emphasis of this research project was to better understand the effects of the task parameters on the distributions of muscle activity. We were therefore interested in eliminating the inter-subject variability. This was accomplished by standardizing the data across subjects so that the variability between subjects would not influence the results. This was accomplished by calculating a mean and a standard deviation for each subject in each experimental condition. The overall mean and pooled standard deviation were then calculated for each condition. Using these values, the individual EMG values were then standardized using the following formula:

$$SV(j, k, l, m) = MP(j, k) - [STDP(j, k) * (M(j, k, l) - AV(j, k, l, m))] / STD(j, k, l)$$

Where:

- SV (j, k, l, m) - standardized EMG value of muscle j, condition k, subject l and repetition m
- AV (j, k, l, m) - actual EMG value of muscle j, condition k, subject l and repetition m
- STDP (j, k) - pooled standard deviation for muscle j and condition k
- STD (j, k, l) - standard deviation for muscle j, condition k and subject l
- MP (j, k) - average for muscle j and condition k
- M (j, k, l) - average for muscle j, condition k and subject l

Model Development

At this point the data was in the form of 32 - {10 X ROW} matrices containing the normalized, standardized EMG values, where 10 refers to the 10 muscles sampled and ROW refers to the number of trials that met the strict criteria laid out for the acceptability of the data based on the position, velocity, acceleration and torque parameters for the trial. The range across experimental conditions for the number of acceptable trials was 102-180. The 32 different matrices refer to the 32 unique combinations of independent variables that each of the subjects performed.

Each of these 32 data sets were then used to generate a set of multivariate distributions. The procedure used is described in greater detail in Stanfield (1993) and is briefly outlined below.

- 1) Determine the first four moments of the distribution for each muscle (mean, standard deviation, skewness and kurtosis) and the correlation coefficients between muscles.
- 2) Develop a lower triangular matrix V such that $V V^T = C$, where C is the {10 X 10} correlation matrix.
- 3) Develop two new standardized {1 X 10} skewness and kurtosis vectors using the following equations:

$$s^* = (V^{(3)})^{-1} * s$$
 where s is the original {1 X 10} skewness vector

$$k^* = (V^{(4)})^{-1} * [k - 6 * \sum_{j=1}^9 \sum_{l=j}^{10} V_{jl}^2 * V_{ll}^2]$$
 where k is the original {1 X 10} kurtosis vector
- 4) Using the above standardized skewness and kurtosis vectors, fit a marginal Johnson distribution to each of the muscle distributions (DeBrotta et al, 1989).

5) Finally, to generate samples that reflect the true multivariate nature of the data use the following relationship:

$$X = S (V * Y) * \mu$$

Where:

X is a {1 X 10} vector of actual multivariate values

S is a {10 X 10} diagonal matrix containing the original standard deviation for each muscle

V is the {10 X 10} lower triangular matrix as described in 2) above

Y is a {1 X 10} vector of samples from the marginal distributions generated using the Johnson distributions developed in 4) above.

μ is a {1 X 10} vector of the original means

Using the above outlined procedure, multivariate Johnson values are generated for each muscle under each experimental condition. With multiple runs of the simulation the shapes of the best fit distributions can be developed.

RESULTS

The results of this simulation are distributions for each of the trunk muscles in each of the experimental conditions. Displayed in Figures 2 - 5 are a small sample of these fitted distributions. Figures 2 and 3 show the best fit distributions for the right erector spinae and the right rectus abdominis muscles while Figures 4 and 5 show the best fit distributions for the right latissimus dorsi and the right external oblique muscles, respectively. Note how this distribution fitting system models even the very skewed distribution of the right latissimus dorsi.

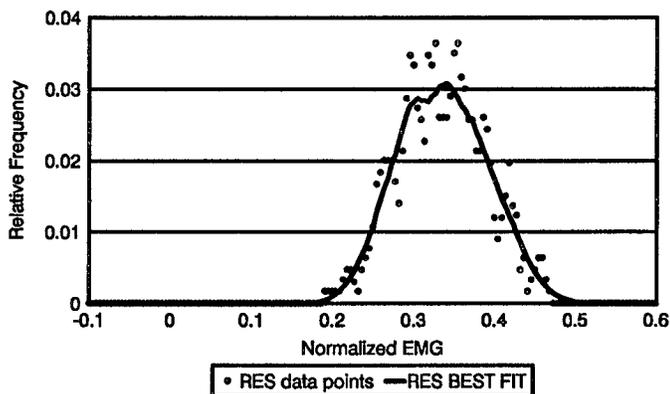


Figure 2. Empirical Data and Best Fit Distribution for the Right Erector Spinae (Sagittal Angle = 40, Sagittal Velocity= 10 deg/sec (isokinetic), Torque = 80 Nm)

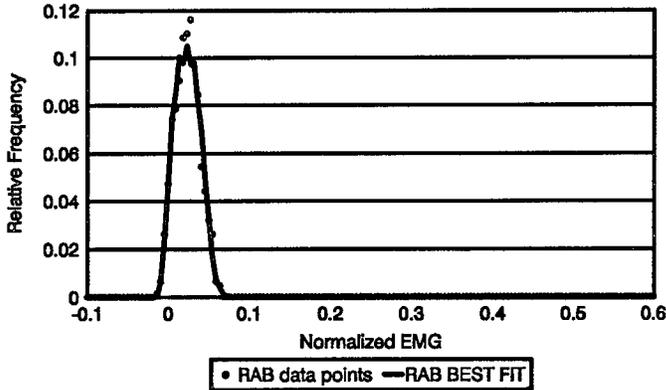


Figure 3. Empirical Data and Best Fit Distribution for the Right Rectus Abdominis (Sagittal Angle = 40, Sagittal Velocity= 10 deg/sec (isokinetic), Torque = 80 Nm)

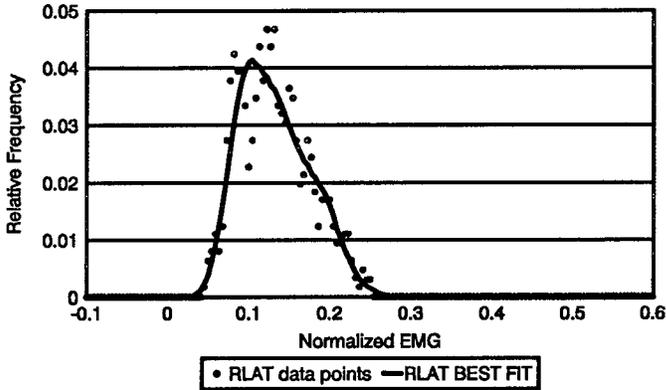


Figure 4. Empirical Data and Best Fit Distribution for the Right Latissimus Dorsi (Sagittal Angle = 40, Sagittal Velocity= 10 deg/sec (isokinetic), Torque = 80 Nm)

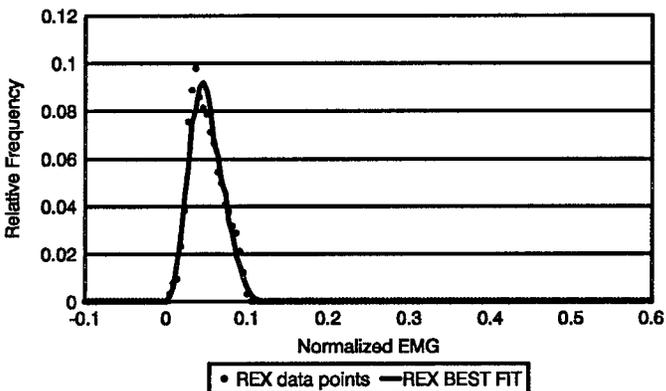


Figure 5. Empirical Data and Best Fit Distribution for the Right External Oblique (Sagittal Angle = 40, Sagittal Velocity= 10 deg/sec (isokinetic), Torque = 80 Nm)

The previous model (Mirka and Marras, 1993) was developed using data from sagittally symmetric lifting postures only. Figure 6 shows the response of this model to an asymmetric condition in this study.

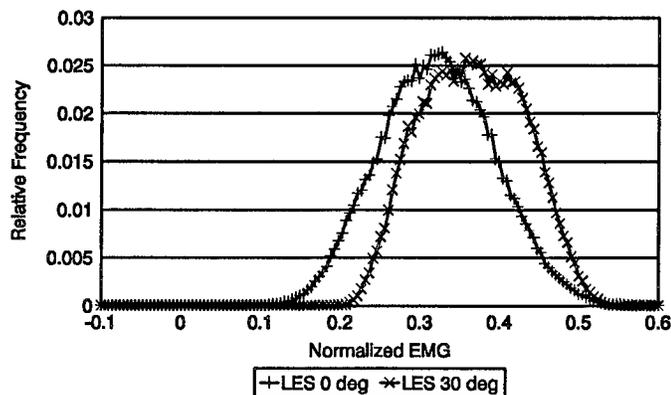


Figure 6. Distributions of the Left Erector Spinae during Symmetric (0°) and Asymmetric (30°) Lifting. (Sagittal Angle = 40° , Sagittal Velocity = 10 deg/sec (isokinetic), Torque = 30 Nm)

DISCUSSION

Many of the biomechanical models of the torso that have been developed rely on electromyographic inputs to drive the model (Granata and Marras, 1993; Marras and Sommerich, 1991a,b; McGill and Norman, 1986; McGill, 1992; Reilly and Marras, 1989). However, it is not practical to collect EMG activity in many industrial environments. The model developed in this research has the capability of generating muscle activities during bending and lifting activities and can therefore act as a motor for these EMG driven biomechanical models. Given a set of environmental conditions (weight, moment, trunk posture and trunk dynamics) this model can produce EMG signals that would be generated during these exertions. These signals could then be input into any of the existing EMG driven model to render estimates of the spine reaction forces.

The model developed in this paper marks a significant improvement over its predecessor (Mirka and Marras, 1993) in that it allows for a true multivariate representation of trunk muscle coactivation. It is believed that as this model continues to develop the predictions of the model are going to more closely reflect the actual muscle activities and therefore our understanding of the trunk muscle coactivation patterns will improve

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