Empirical Evaluation of Models Used to Predict Torso Muscle Recruitment Patterns

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(ABSTRACT)

For years, the human back has puzzled researchers with the complex behaviors it presents. Principally, the internal forces produced by back muscles have not been determined accurately. Two different approaches have historically been taken to predict muscle forces. The first relies on electromyography (EMG), while the second attempts to predict muscle responses using mathematical models. Three such predictive models are compared here. The models are Sum of Cubed Intensities, Artificial Neural Networks, and Distributed Moment Histogram. These three models were adapted to run using recently published descriptions of the lower back anatomy. To evaluate their effectiveness, the models were compared in terms of their fit to a muscle activation database including 14 different muscles. The database was collected as part of this experiment, and included 8 participants (4 male and 4 female) with similar height and weight. The participants resisted loads applied to their torso via a harness. Results showed the models performed poorly (average R^2's in the 0.40's), indicating that further improvements are needed in our current low back muscle activation modeling techniques. Considerable discrepancies were found between internal moments (at L3/L4) determined empirically and measured with a force plate, indicating that the maximum muscle stress selected and/or the anatomy used were faulty. The activation pattern database collected also fills a gap in the literature by considering static loading patterns that had not been systematically varied before.

DEDICATION

To God, who provided all the pieces of the puzzle, who's given me this life and a wonderful group of people to share it with.

To my wife, for providing me always something to look forward to: her love.

To my parents, for their unconditional love and support, and for letting me make my own decisions.

To my friends, for each of you is an indispensable part of my life.

To my past and future teachers and mentors, because each of you has influenced me deeply in ways you probably can’t imagine. You have also shown me the most beautiful profession in the world, one which I look forward to serving in.

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Finally, this work would not have been possible without eight persons who gave me their time and effort. Although they shall remain anonymous, thanks to the participants of this experiment. After all, what you will see here is in a sense a part of them.

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Chapter 1. INTRODUCTION

1.1 Epidemiological Motivation

The human spine, including the muscles that act upon it, is a complex system that includes structural body support as one of its many functions. Injuries to this system that result in pain are collectively identified as back pain, which is one of the most common and significant musculoskeletal problems in the United States (Hollbrook, et al., 1984; Praemer, et al., 1992). Estimates of its costs are on the order of tens of billions of dollars annually (NIOSH, 1997; Cats-Baril and Frymoyer, 1991; Frymoyer et al., 1983), although the predicted amounts vary widely. These costs are distributed over a large number of cases, with some epidemiological studies estimating back pain as the prevalent symptom in around 50% of all reported musculoskeletal diseases (NIOSH, 1997; Praemer, et al., 1992).

A subclass of back pain is Low Back Pain (LBP), which refers to pain in the lumbar region of the spine. The risk of LBP has been associated with industrial work for some time (Andersson, 1981), especially with Manual Materials Handling (MMH) tasks, which include lifting, lowering, pushing, pulling, holding and carrying materials (Marras, 1997). Estimates of the incidence of occupationally induced low back pain range from 1 to 15% annually, varying with occupation (Kelsey and White, 1980). MMH aspects that have been identified as risk factors include the weight of the item being carried and the distance the object is held from the body. Both of these aspects directly affect the tissue loads in the lumbar spine area. For example, workers that are required to lift heavy loads develop low back disorders about eight times more frequently than workers performing sedentary work (Chaffin and Park, 1973).

Partially to address the issue of LBP, NIOSH has created their Lifting Guides, which attempt to quantify the risk of injury that MMH tasks pose to the persons performing them (NIOSH, 1981; Waters, et al., 1993). Not coincidentally, the Lifting Guides are designed in part to assign lower injury risks to MMH tasks that result in lesser compression forces in the lumbar spine. These guides, however, have been criticized on their dependence on multiple criteria (i.e. biomechanical, epidemiological, psychophysical, and physiological), thus, their validity depends on the validity of the criteria used (Dempsey, 1998). According to Dempsey (1998), validation of criteria is one of the most critical MMH research needs. He suggests that the validation process must develop quantitative relationships between risk factors and the probability or severity of low back injury. The next section presents an overview of the biomechanics field and its approach to the development of these relationships.

1.2 Biomechanics

Biomechanics attempts to link task conditions with the loading of internal tissues. When the loading of the internal tissues is known, it can be compared against the tissue's tolerance to the loads. The field combines knowledge of human anatomy, human tissue composition, neural control theory, mechanics and dynamics (among others) to create models that mathematically represent the inner workings of the human support and movement systems. These models include those that describe lumbar muscle recruitment patterns under different load conditions.

At this point, it is important to discriminate between the definitions of force, moment, and load used in this work. A force is a vector (i.e. with direction) quantity that describes the linear (e.g. push, pull) effect of one body upon another. A moment is also a vector quantity, but it is the result of the torsional effect of a force over a certain distance. Load will be the combination of forces and moments that act upon a specific area. Using this terminology, a force in the hands of a person (e.g. the weight of an object) causes both a force and a moment on the lumbar spine (due to the distance between the force and the spine). The combination of this force and this moment is the load on the lumbar spine.

The main problem faced by biomechanics when modeling the low back is the complexity of this system. Although spinal compression forces caused by external disturbances can be easily and accurately calculated, the total compression in the spine is also a function of the muscle reactions to equilibrate the external moment. These muscle reactions (i.e. tension forces) are relatively large because they must counteract the external moments using relatively small moment arms (i.e. these muscles are significantly closer to the spine than is the external force). However, the accurate calculation of muscular reactions is hindered by the complexity of the spine.

The intricacy of the spine arises in part out of the large number of muscles that cross this region and their multiple attachment points to the spine, which complicate the determination of their lines of action (i.e. the direction of the force they generate). These two factors, among others, make the accurate prediction of muscular forces impossible without the use of assumptions. These assumptions, in turn, reduce the internal validity of the models developed, that is, their ability to represent the system using the system's own parameters. The ongoing search in this area of biomechanics is, then, the development of models that require the least number of assumptions, and whose assumptions are physiologically valid. These models would serve as 'bridging technologies" between the risk factors present in a task and the probability of injury the particular task represents. These technologies, in turn, would partially fulfill Dempsey's (1998) requirement for quantitative relationships between risk factors and the probability or severity of low back injury.

Currently, however, the low back injury mechanism remains unclear. It is still unknown whether low back injuries occur because of high tissue loads in the spine, or because of spinal instability, or because of their combination (Cholewicki and McGill, 1996). In this context, "bridging technologies" are affected by several problems, including the validity issues discussed above. Section 1.4 addresses the current state of these technologies, with particular focus on new developments. Before exploring these models, however, it is useful to summarize our knowledge of lumbar muscle recruitment patterns.

1.3 Lumbar Muscle Recruitment

The exploration of lumbar muscle recruitment is hindered by our inability to measure the forces on the tendons of the muscles acting on this area. The ethical dilemma of this notwithstanding, this is very difficult for two main reasons. The first is that a considerable number of aponeuroses (i.e tendon-bone attachment sites) exist, some of them distributed over several vertebra. Thus, a large number of force transducers would have to be placed and monitored. This leads to the second problem, which is that such a procedure would be highly intrusive and, thus, interfere with the natural recruitment patterns. Research on animals using this approach is limited, at least for the lumbar region, because no other animal has a vertebral column that is both structurally similar to that of humans and used in a comparable fashion (Bogduk, et al., 1992a).

We are, thus, currently limited in our ability to study these patterns to inferential methods. The main inferential method used for the determination of lumbar muscle recruitment patterns is surface electromyography (EMG). This technique involves the collection of an electrical signal from electrodes placed on the skin over the muscle being studied. This electrical signal represents the combination of several muscle action potentials that are generated during the activation of the muscle. Although the exact EMG-force relationship is unknown, it is generally accepted that EMG signals, when properly collected and analyzed, are monotonically correlated with force. In this respect, the method is inferential, because the researcher must infer that the muscle generates a certain amount of force based on the EMG signal. It also requires the assumption that the signal collected represents the overall activation of the muscle of interest.

These drawbacks notwithstanding, the technique is very useful to observe patterns of activation instead of actual muscle forces, and has been widely used to study lumbar muscle activity during static torso loading. The best known studies of this region are those performed by Lavender and colleagues. In these studies, the EMG activity levels of the largest superficial lumbar muscles were monitored while participants in symmetric and asymmetric postures generated lumbar moments to counteract external loads varying in orientation (Lavender, et al., 1992a, 1992b, 1992c, 1993a, 1993b, 1994, 1995). Overall, the studies found that moment magnitude and direction, as well as their interaction, significantly influenced the normalized muscle EMG signals. In addition, increased EMG activities were observed for asymmetric postures.

The interpretation of EMG signals in dynamic tasks is much more difficult. For example, McGill (1992) found inconsistent changes in muscles activities as participants rotated their torso against a load with different levels of spinal lordosis. He attributed the inconsistency to an increased effect of passive tissues when the participants deviated from a neutral upright position. Usage of EMG signals in dynamic tasks is debatable, since any skin movement will affect the position of the electrode with respect to the muscle, potentially altering the portion of the muscle being sampled by the electrode, and, consequently, the resulting signal. Still, Mirka (1991) suggests that if the proper precautions are taken, EMG signals can be collected with confidence in controlled dynamic exertions. This idea, however, is not supported by some research, which suggests that dynamic exertions require careful study of muscle force-length and force-velocity relationships (Baildon and Chapman, 1983; Redfern, 1992).

Trunk muscle coactivation, or cocontraction, has also been found in studies of lumbar muscle recruitment. This phenomena refers to the observation of significant activity levels in muscles that can’t, based on their lines of action, generate moments that counteract the external moment applied to the spine. Thus, these muscles generate moments that are added to the external moment and therefore require additional activation in other muscles. Mathematical definitions of the coactivation phenomenon have been proposed (see Hughes, 1991) due to the fact that in complex motions, the muscles acting as agonists and antagonists may not be obvious. The effect of cocontraction in lumbar muscles does not appear to be negligible. Some researchers estimate that coactivation may increase spinal compression as much as 45% (Granata and Marras, 1995b). The mechanisms that control it, however, are currently unknown, although some association with spinal stability has been proposed.

Some researchers have collected their own lumbar EMG data to correlate it to their lumbar model formulations (e.g. Ladin, et al., 1989). However, usually the data is not completely reported. As is the case with the Lavender studies, only averages are reported (with limited variability measures). Other researchers have opted to use the Lavender data in the development of their models (e.g. Nussbaum, et al., 1995; Raschke, et al., 1996).

Although these efforts have certainly been useful in our exploration of lumbar muscle recruitment, drawbacks exist. First, the report of averages, with limited data on variability, makes evaluation of inter-subject differences in recruitment difficult. In addition, lack of trial repetitions eliminate any possible analysis of intra-subject differences in recruitment. The range of loads studied is also small; the upper load limits (based on Maximum Voluntary Exertions, MVE's) are completely avoided. Furthermore, sample sizes are small (<10) and in some cases limited to males only. These characteristics restrict the generalization of the results. Possibly the largest drawback, however, is the limited inclusion of torsional moments in the experiments. For our knowledge of lumbar muscle recruitment to be complete, data from combinations of torsional moments with sagittal and frontal moments are needed.

The next section discusses some of the models that attempt to bridge the gap between external loading and internal tissue reactions. All of them relate to lumbar muscle recruitment in one of two ways; they either use the empirical patterns obtained to estimate muscle forces or they attempt to predict lumbar muscle activation patterns.

1.4 Low Back Muscle Activation Models

Although simple in principle, implementing the "bridging technology" approach described before is extremely difficult (if not impossible) for two reasons, at least if an exact solution is desired. First, direct measurement of loads *in vivo* is difficult with current technology, paradoxical in its approach, and unethical as judged by our society's standards. It would require intrusive instrumentation and major surgical procedures to implant the measuring devices. The paradox lies in that the particular subject in which the devices are implanted would no longer be a healthy individual, and measurements taken would not be representative of a standard population.

The second problem affects the use of exact mathematical approaches to obtain a solution based on the laws of statics and dynamics. Even simple anatomical models of the lumbar region identify at least eight muscle groups. Since only six equilibrium equations are available, the system is statically indeterminate, and an infinite number of mathematical solutions exist.

Therefore, *in vivo* and exact mathematical approaches have to be discarded and other approaches have to be used to predict muscle activation. The development of these empirical bridging technologies has been researched for quite some time, with models progressing from static, two dimensional analysis, to dynamic, three dimensional computer models (Granata and Marras, 1993; Chaffin and Andersson, 1991).

Contemporary lumbar biomechanical models are grouped into two main areas. The first area uses empirical measures of muscle activity (e.g. EMG data) to estimate resultant muscle forces. The second area involves the creation and validation of computer models that *predict* muscle activation levels.

At this stage, a discussion on the validation of these models is warranted. Direct validation (*in vivo*) of these models is currently impossible, for all the reasons outlined before. To a limited extent, indirect validation of predictive models can be performed if the assumption of a monotonic EMG-force relationship is made (i.e. increasing EMG means increased force levels). Since these models are tailored to prediction of EMG signals, comparisons can be made between empirical and computed values. Force estimating models that use EMG as an input, however, can't be even indirectly validated with EMG, since they already are using the validation measure as an input. The creators are left with, as the only "validation" recourse, the comparison of model parameters and results with known (or even estimated) physiological limits (Granata and Marras, 1993; Granata and Marras, 1995a; McGill and Norman, 1985; McGill and Norman, 1986), for example, muscle stress; or with the comparison between applied moments and the reactive moments generated by the EMG model. Given these difficulties Cholewicki and McGill (1996) propose a validation approach that consists of component validation, internal validity checks, sensitivity analysis, and judgmental evaluation. Still, the reader should be aware of the difficulty (or even impossibility) in directly validating the models discussed next. Although their creators may describe validation processes the models went through, these, at best, are only indirect.

Three innovative predictive models have been proposed in recently published literature. They are a modified feed-forward neural network with error back-propagation (Nussbaum, et al., 1997; Nussbaum, et al., 1995), distributed moment histogram (Raschke, et al., 1996), and optimization with a cubed muscle stress cost function (Crowninshield and Brand, 1981; Hughes, et. al., 1994; van Dieen, 1997). Each of these, together with EMG models, merits more detailed consideration, presented in the following sections.

1.4.1 Models Based on Electromyographic Data.

Electromyography is the measurement of the electrical activity of a skeletal muscle using an electrode placed on the skin or introduced into the muscle (Marras, 1997). EMG-based models use this data as a representation of muscle activity (Granata and Marras, 1993; Granata and Marras, 1995a; McGill and Norman, 1985; McGill and Norman, 1986; Nussbaum and Chaffin, 1998). The EMG readings are usually normalized against individual maximum voluntary exertions (MVE's) and corrected for the effects of several muscle properties particular to the situation under study (e.g. muscle length, contraction velocity). Although continually improving, these models suffer from two main drawbacks. The first is their validation process, discussed previously. To further compound the validity problem, some of the EMG-based models also include non-physiological parameters that compromise their internal validity (as noted by Nussbaum and Chaffin, 1998).

The second drawback suffered by these models concerns their application. In order to gather input data to run an EMG-based model, participants have to be instrumented with electrodes on several parts of their body. Furthermore, these electrodes have to be connected to sensitive electrical equipment. These reasons make the use of EMG-based models in field environments difficult. This, combined with dependency on EMG measures, make their usability in design situations very limited.

The main advantage of these models lies in their ability to develop muscle force estimates that agree with EMG data for dynamic exertions (including antagonism). They are often singled out as well for being able to capture the recruitment patterns of specific individuals. However, since one of their inputs is the EMG data of a specific individual, such abilities exist only because the force generation signal tracks the EMG signal. Since predictive models do not have this advantage, it can be argued that they have to model the underlying physiological control mechanisms that direct dynamic exertions. While criticized by some researchers for their poor performance in dynamic exertions (Marras, 1997), it can be argued that, as the predictive models evolve, they might model these physiological dynamic control mechanisms better.

1.4.2 Feed-forward Neural Network with error Back-propagation

Artificial Neural Networks (ANN's) are an artificial representation of biological networks of neurons. They consist of a group of individual processing units that are highly interconnected. ANN's are used in many different fields, but few applications have been developed in biomechanics. The applications in biomechanics that have been developed have usually been restricted to the arm or leg (Lester, et al., 1997; Savelberg and Herzog, 1997). Some earlier modeling work also shows some basic neural network implementation (Caldwell and Chapman, 1991).

The first generation of the neural network described here (Nussbaum, et al., 1995) is a standard multi-layer feed-forward neural network with error back-propagation. It is shown in Figure 1. The network is fully interconnected. The inputs to this network are the magnitudes of the external moments, while the outputs are the muscle activation levels for each of the eight lumbar muscles considered in this study. Each of the nodes in the network receives several signals, which the node combines to generate its output. The input nodes receive only one signal, however. A unit's net input (net_i) is determined using the following formula.

$$net_i = \sum_j a_j * w_{i \leftarrow j} \qquad (1)$$

where,

j	indexes all units that connect to unit i
a_j	activation level of unit j
$w_{i \neg j}$	weight of connection from j to i

A unit's output can be calculated once its net_i is calculated. Formula 2 shows the activation function.

$$a_i = \frac{1}{1 + e^{-(net_i + bias_i)}} \qquad (2)$$

where,

i	identifies the node
$bias_i$	variable term applied to unit i
net_i	see formula 1
a_i	resultant activation for node i

The activation process for the networks works as follows (see Figure 1). Once an input signal is provided to the input nodes, the signal is fed forward to the hidden layer, which combines the inputs according to equation 1. Once all the net inputs to the hidden layer are calculated, the activation for each node is computed with equation 2. These serve as input signals to the muscle (output) layer, which use the same process to determine their activation.

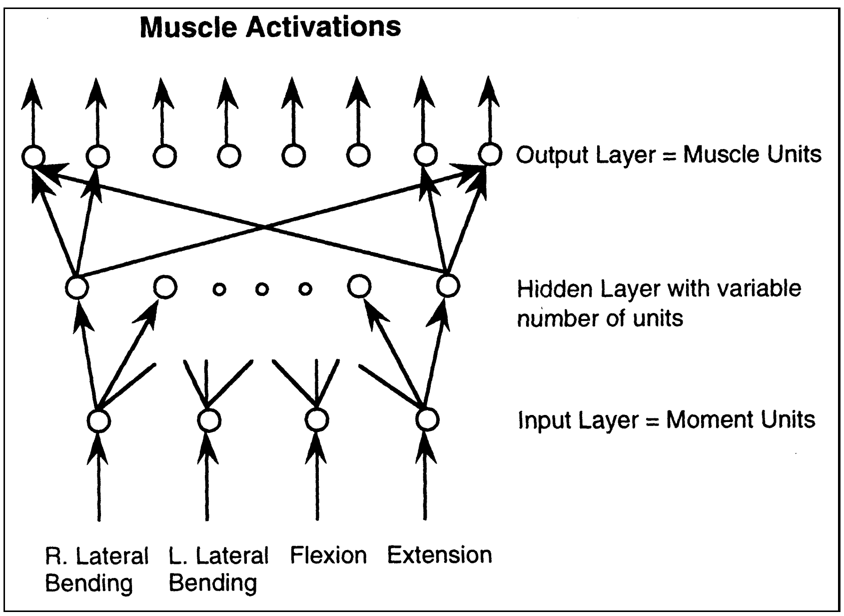

Figure 1. Illustration of the basic network model used (from Nussbaum, et al. 1995)

The model used in this manuscript is a modified multilayer feedforward network with error back-propagation, fully described in Nussbaum, et al. (1997). The network is illustrated in Figure 2. Several differences can be observed when it is compared to the first generation neural network. First, it has inputs for all three external moments. Second, it adds another layer after the muscle layer. This layer represents the output (reaction) moments as determined by the network. Other differences can't be observed based on the diagram. First, the weights between the muscle layer and the output layer are fixed, and predetermined, and represent each muscle's moment contribution for each direction. Second, the nodes in the muscle layer have connections between themselves (Inhibition) and into themselves (Self-inhibition). This is illustrated in Figure 3.

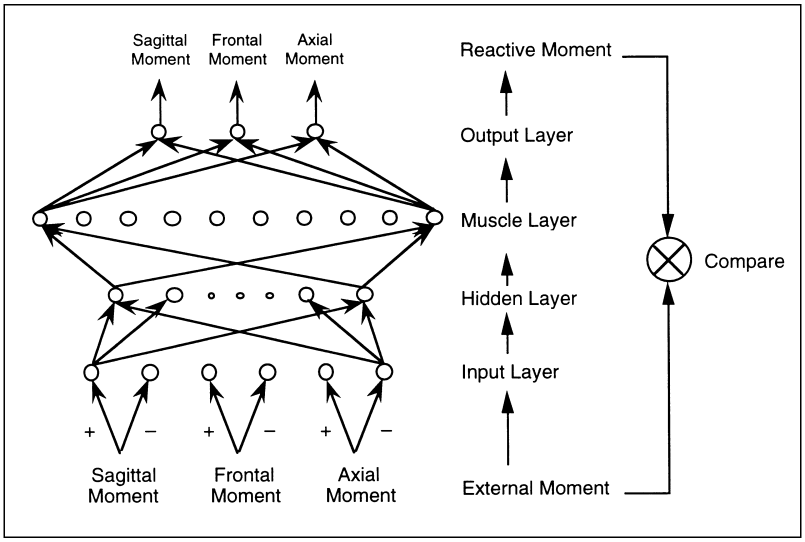

Figure 2. Modified multi-layer neural network (from Nussbaum, et al. 1997)

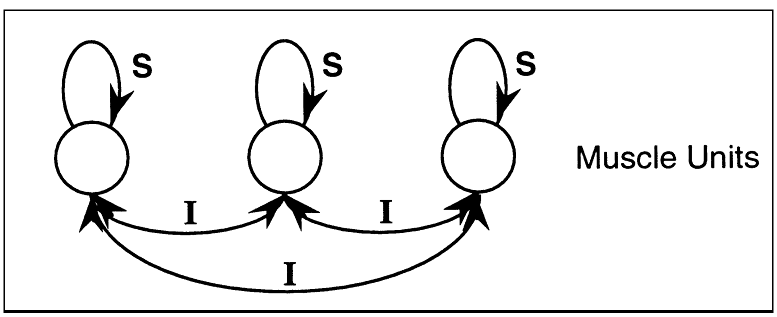

Figure 3. Illustration of the Inhibition and Self Inhibition concepts (from Nussbaum, et al. 1997)

Based on these additions, the muscle layer calculation of its net input changes to the following formula (equation 3):

$$net_i = \sum_j a_j * w_{i \leftarrow j} - \sum_{k \neq i} I a_k - S a_i \qquad (3)$$

where,

j	indexes all units that connect to unit i
a_j	activation level of unit j
$w_{i \neg j}$	weight of connection from j to i
I	Inhibition value
a_k	activation level of unit k

S Self-Inhibition value
a_i activation level of unit i

The activation equation (2) applies to all the layers except the output layer. For the output layer, the net input is the same as the output. The process for determining the network's activation state follows.

The input units, located in the input layer, receive the external spine moments. These are transferred, through weighted connections, to the next layer (first hidden layer). The units in the first hidden layer take their inputs from all their input connections (equation 1), and pass the result through an activation function (equation 2), which returns their activation level. This level, in turn, is passed through weighed connections to the second hidden layer.

The second hidden layer is different from the typical feedforward layer because it is competitive (i.e. units are not only connected to the previous and next layers, but also between themselves, as shown in figure 3). Therefore, the activation of other units in the layer is considered when determining the net input. In addition, each unit has a connection, called by Nussbaum, et al. (1997) Self-Inhibition, that goes into itself. This connection is also considered in determining each unit's input. Once again, once the input to each unit is calculated, it is processed through an activation function. Each unit in this layer represents a muscle group which is previously known, as weights from this layer to the output layer are known and pre-determined, and represent the moment contribution of each muscle group to each moment direction.

Activation levels are passed through weighted connections to the output layer. The output layer, however, does not process its input through any activation function. Thus, each unit's input is equal to its activation level. Again, the activation of these units represents the reaction moments predicted by the model.

Before this neural network is useful, however, it has to be trained. The training process involves the modification of the weights between layers. The training process is described in Nussbaum, et al. (1995, 1997). It presents the network with a training pattern, determines unit activation levels with the current weights, and propagates any errors backward in the network (i.e. contrary to the direction in which the output was calculated), so the term back-propagation is used. Haykin (1994) discusses the algorithm, including its derivation, in detail. The weight modification process is performed based on equation 4, shown next.

$$\Delta w_{i \leftarrow j}(n+1) = e(d_i * a_j) + m\Delta w_{i \leftarrow j}(n) \quad (4)$$

where,

j	indexes all units that connect to unit i
a_j	activation level of unit j
$w_{i \neg j}$	weight of connection from j to i
n	cycle number
m	momentum term (effect of previous weight changes on current weight changes
e	learning rate
d_i	error signal for the layer

Weights between the muscle layer and the output layer are not modified because they are indicative of the anatomy assumed, which remains fixed. It is important to emphasize that training of a neural network is an iterative process.

ANN-based models are predictive, and have been proven to generalize particularly well to loading conditions that were not included in their training set (Nussbaum, et al., 1995). They can be easily adapted to model individuals by modifying the fixed weights between the muscle and outputs layers. Their disadvantage lies in the computationally intensive training process they have to go through. Also, their performance with dynamic loading conditions is still untested. However, the ANN approach described here has one advantage over the other models considered: it is able to account for intra- and inter- subject variability in its current form. Inter-subject variability can be addressed with the use of different anatomies for different subjects. Intra-subject variability is handled by randomness in the order of the determination of muscle layer activation, combined with the Inhibition and Self-Inhibition parameters. Although intra- and inter- subject variability may be accounted for in the other models using other approaches (see the discussion section for each, 1.4.3 and 1.4.4), they are unable to account for them in their *current* forms.

1.4.3 Distributed Moment Histogram.

The Distributed Moment Histogram (DMH) proposed by Raschke, et al. (1996), postulates that muscle activation patterns can be predicted by basing muscle recruitment on the activity distributions exhibited by motor cortex neurons. These neurons have been linked with motor control functions (Brooks, 1986). Georgopoulos, et al. (1983) studied the effects of direction, amplitude and peak velocity of tracking arm movements on the firing rate of neurons in the motor cortex of primates. They found statistically significant relationships between neuron firing rates and these parameters, that is, the firing rate of specific neuron groups could be correlated with movement characteristics. Further investigation has allowed the classification of neuron groups according to their "preferred direction", that is, the movement direction of a particular body part in which they fire at a peak rate (Brooks, 1986). These neurons have also been found to remain sensitive to a considerable range of orientations (300°, Brooks, 1986).

Later studies (Georgopoulos, et al., 1989) elaborate on these principles and correlated arm rotations (on both primates and humans) with the rotation of what they call a neuronal population vector. This vector is the weighted sum of contributions of directionally tuned neurons, that is, neurons that have been found to fire at a peak rate when the limb is oriented in a particular direction. The population vector is calculated by multiplying a normalized firing rate by a vector representing the preferred direction of a particular neuron and summing the results over a range of neuron cells. This implies that neurons will fire even when the direction of movement is not their "preferred" one. This firing pattern is described by Brooks (1986) as being bell shaped. The studies described previously, however, were performed only for limb movements. At the time of this writing, no study linking the lumbar spine and the motor cortex could be found.

Raschke (1994) suggests, based on these investigations, that the central nervous system does not select individual motor units to perform a movement, but rather selects a distributed pattern of them that follows the firing pattern distribution and centers around the desired force direction.

The DMH model locates muscles on a polar graph according to their position on the trunk's circumference (see Figure 4). The height of the polar vector representing each muscle in the graph represents the product of the muscle cross-section, its moment arm, and its directional component in the longitudinal axis (Equation 5).

$$h_i = z_i * CSA_i * MA_i \qquad (5)$$

where,

h_i = polar vector magnitude for muscle *i*
z_i = z component of the line of action of muscle *i*
CSA_i = cross sectional area for muscle *i*
MA_i = moment arm of muscle *i* for the given load direction

Once the graph is set-up, a reaction moment equal in magnitude and opposed in direction to that caused by the external loads (i.e. offset by 180 degrees) is plotted. The distributed moment histogram is then plotted with the reaction moment in its center (see Figure 5).

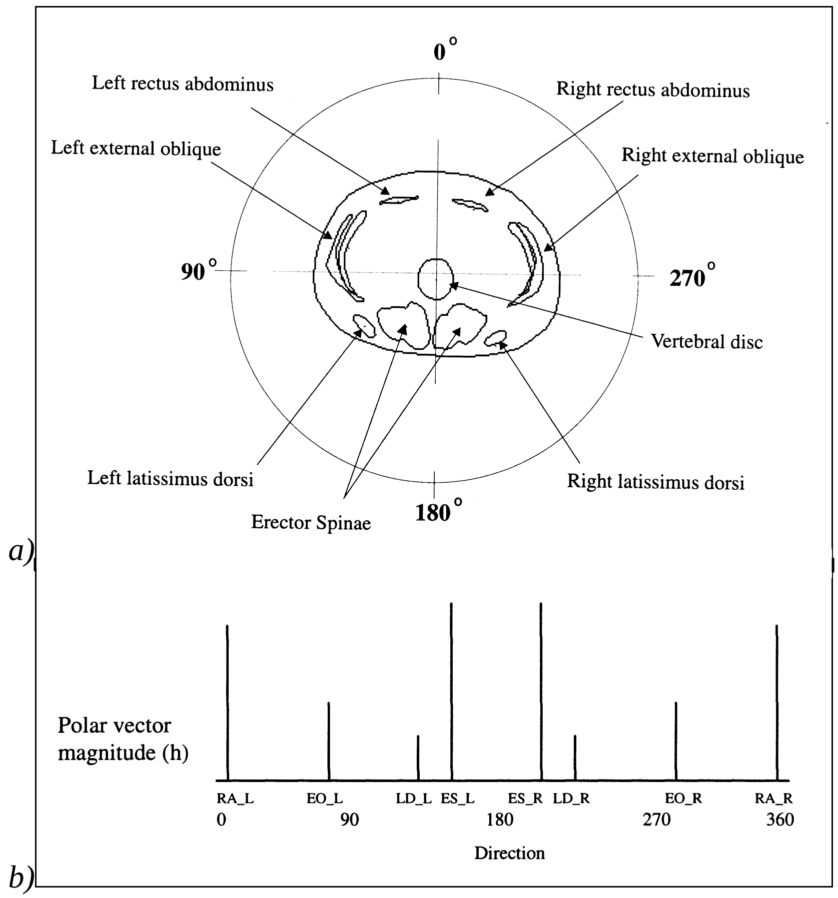

Figure 4. Transformation of global coordinates into a polar system. (a) illustrates the lumbar cutting plane and angle definitions used. (b) illustrates the hypothetical polar graph (from Raschke, et al., 1996).

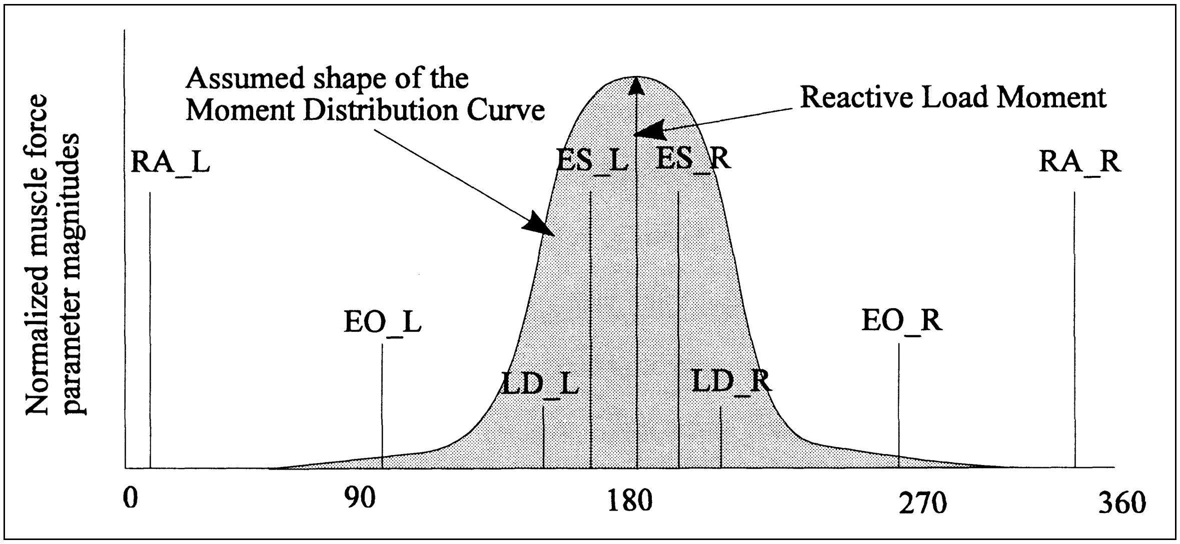

Figure 5. Distributed Moment Histogram superimposed on the vector magnitudes shown in Figure 4b (from Raschke, et al., 1996).

The spread of the moment was chosen to be Gaussian with the width of the distribution estimated using the myoelectric data of Lavender, et al. (1992c). Raschke (1994) examined spreads that ranged from 180° to 320° and concluded that the model was fairly insensitive to the distribution width when examining the erector spinae, latissimus dorsi, external oblique and rectus abdominis muscle groups. In his subsequent testing with these muscle groups, he used a spread of 300°.

Once the distribution is plotted according to its height and width characteristics, each muscle's internal moment contribution is calculated as the product of its magnitude in the polar graph (h_i) and the distributed moment histogram value at the orientation of muscle *i* (Equation 6).

$$SF = \frac{\text{Moment Applied}}{\sum_{i=1}^{n} a_{\mathrm{i}}} \qquad (6)$$

where,

SF	= scaling factor
α_i	= product of h_i and the distributed moment histogram value at angle of muscle *i*
n	= number of muscles included in the model

The scaling factor is used to gradate the different muscle contributions to equilibrate the moment applied (Equation 6). The scaling factor accounts only for the arbitrary scaling of the moment distribution curve, that is, it has no physiological association (Raschke, 1996). Its use seems to be justified based on the distributed moment histogram's base on neural firing patterns. The scaling factor could then be considered a relationship factor between these firing rates and the actual activation of the muscle motor units.

After the scaling factor is found for the particular loading situation, the tensions of each muscle are calculated using Equation 7.

$$F_i = \frac{SF * a_i}{MA_i * z_i} \qquad (7)$$

where,

F_i	= estimated tension of muscle *I*
SF	= scaling factor
α_i	= product of h_i and the distributed moment histogram value at angle of muscle *i*
MA_i	= moment arm of muscle *i* for the given load direction
z_i	= z component of the line of action of muscle *I*

A computational problem may arise at this point, because the calculated muscle activation may cause small reactive lateral and torsion moments that were not present in the loading condition. The solution used by Raschke (1999, Personal Communication) is to begin a new iteration of the model with the lateral and torsion moments included until convergence is found.

The DMH model described up to this point is able to handle moments from the sagittal and lateral directions only (i.e. no "twist' moment). However, the mathematical implementation of the model does handle twist moments (Raschke, 1999, Personal Communication). When a twisting moment is introduced, the model modifies activities of the oblique muscles, based on the empirical findings of McGill (1992).

Raschke (1994, 1996) evaluated the model with participants performing a dynamic trunk extension task (velocity less than 30°/s). He reports that the model corresponded acceptably with measured EMG data for the agonist muscles studied (erector spinae, R^2=0.91; latissimus dorsi, R^2=0.4), even under these moderately dynamic conditions. The DMH model also predicted to some extent the antagonistic activation of the external oblique, although poorly (R^2=0.07).

Although the R^2 value for this muscle was low, Raschke reports that the DMH model was able to predict a baseline antagonistic activation. These performance levels are similar to those reported by Raschke (1994) for the Bean, Chaffin and Schultz (BCS; Bean, et al., 1988) model, an optimization based model, in a comparison study, although the BCS model did not predict a baseline activation for the external oblique.

Based on the previous discussion, the DMH model seems computationally simple, and appears to have a direct physiologic analogy. It has the capability to account for three-dimensional moments (i.e. including twist), although the method used to account for twist moments departs from the theoretical DMH model. Its performance for a wider set of muscles and over a larger set of loading conditions remains to be tested, however. In terms of inter-subject variability, the model should account for these if different anatomy sets are used for each subject. Intra-subject variability, however, can't be addressed by the model in its current form, since the moment distribution is fixed for all runs. The model might be able to account for this type of variability with the introduction of a randomness element into its moment distribution parameters.

1.4.4 Optimization with a Cubed Muscle Stress Cost Function (SCI model).

The optimization modeling approach assumes that the central nervous system optimizes (by minimization or maximization) certain criteria, known as objective functions, while complying with several constraints. These constraints usually include a balance of moments or forces on the spine, accompanied by certain others that vary depending on the objective function. Mathematically, the general model is expressed as follows,

$$\text{minimize} \quad \sum_{j=1}^{n} c_j x_j \qquad (8)$$

subject to:

$$\sum_{j=1}^{n} a_{ij} x_j \geq b_i, i = 1,2,..., m$$

$$x_j \geq 0, j = 1,2,..., n$$

where x represents the variables of interest, c represents a certain cost associated with each x, and a represents constraint factors.

Throughout the years, many objective functions have been proposed, with different degrees of success. For instance, Seireg and Arvikar (1973) minimized the sum of contraction forces, Gracovetsky and Farfan (1977) minimized the shear forces on the spine, Crowninshield and Brand (1981) minimized the sum of the cube of the muscle intensity, An et al. (1984) and Crowninshield (1978) minimized the muscle intensity, Schultz et al. (1983) approximately minimized the muscle contraction intensity and the spine joint compression force, and Bean, et al. (1988) minimized two separate linear objective functions, muscle intensity and joint compression force (based on Schultz et al., 1983).

The sum of cubed intensities (SCI) model presented in van Dieen (1997), which was originally developed by Crowninshield and Brand (1981), uses a constrained non-linear optimization process to solve the lumbar muscle recruitment problem and estimate muscle activation and/or forces. The SCI optimization process minimizes the sum of the cubed muscle intensities. The constraint function consists of zeroing the difference between the predicted and actual spinal moments. Hughes et al. (1994) and Hughes (1991) found the SCI optimization model to perform best among several other optimization functions for the torso musculature. The model's mathematical formulation is shown next.

minimize

$$\sum_{j=1}^{m} act_j^3 \qquad (9)$$

subject to:

$$\mathbf{Mnet} = -\sum_{j=1}^{m} [(g * pcsa_j * act_j) * t_j \times \mathbf{r}_j] \pm tol$$

$$\mathrm{F}_j \geq 0, \quad \mathrm{F}_j \leq \mathrm{F}_{\max}, \; j = 1 \ldots m$$

$$\mathrm{F}_{\max j} = g * pcsa_j, \; j = 1 \ldots m$$

where act_j is the activation of muscle slip j, **Mnet** is the three dimensional joint torque, $pcsa_j$ is the physiological cross sectional area of muscle slip j, $\boldsymbol{t}_j$ represents the direction of the muscle's line of action, $\mathbf{r}_j$ is the moment arm of the muscle with respect to a center of vertebral rotation, *tol* is the error limit, g is the maximum stress allowed at the muscle slips, F_j is the predicted force, $F_{\max j}$ is the maximum force that can be produced, and m is the number of muscles used in the model.

Optimization models have been criticized in the literature because of their alleged lack of ability to predict cocontraction. However, although this might have been a problem with other optimization models, the SCI model has been shown to predict cocontraction of trunk muscles under certain conditions (van Dieen, 1997; Hughes, 1991). It is possible, then, that previous optimization models failed to predict coactivation because they optimized the incorrect objective function. Optimization models are also criticized for being generally poor predictors of muscle activation when dynamic conditions exist (Mirka and Marras, 1993; Marras and Mirka, 1992; Marras and Mirka, 1990). Still, the model described here has been proven to correlate very well with real EMG data (van Dieen, 1997) collected during static exertions, which will be the focus of this work. The implementation of the model is relatively simple if one has the non-linear optimization routines available. Inter-subject variability can be accounted for in the SCI model by changing the anatomy used. Intra-subject variability, however, can't be addressed by the SCI model in its current form, because it will return the same muscle activation patterns for all trials of the same loading condition. Three dimensional loads can be handled by the model.

1.4.5 A note on model anatomy.

As may be inferred from the previous discussion, all biomechanical models have, in one way or another, a direct dependency on anatomical data of the low back region. McMulkin (1996) evaluated several optimization models while using two different anatomies of the lumbar region. He found significant differences in optimization models predictions when the two anatomies were varied. When the models described before have been published in the literature, their anatomical assumptions are not always clear. Therefore, anatomy may present a large confounding factor if direct comparison of these models is made out of their published forms without any regard for the anatomy used.

To minimize the effects that anatomy might have in the comparison between the models, all three, ANN, DMH and SCI, will use the same anatomical database. This database is described by van Dieen (1997). The joint center of rotation coordinates, as well as the data for the back muscles and psoas major muscle were derived from studies by Bogduk, et al. (1992a, 1992b), based on the compilation of Stokes and Gardner-Morse (1995). Data from the rectus abdominis and oblique abdominal muscles were derived from McGill (1996). Data for the latissimus dorsi was derived from Cholewicki and McGill (1996).

The anatomy used in this work will consider 7 pairs of muscles: internal oblique, external oblique, rectus abdominis, multifidus, longissimus thoracis, latissimus dorsi, and iliocostalis lumborum. The relevant anatomical data for the muscles mentioned above is shown in table 1. The muscles chosen are based on version A of the models evaluated by van Dieen (1997). Although he includes the psoas major in the group, this muscle will not be considered here due to its low generation of significant spinal moments (Bogduk, et al., 1992b) and difficulty in measuring its EMG activity with surface electrodes. The latissimus dorsi muscles are included because of the low correlation the ANN, DMH, and SIC model predictions have had with its EMG data. The muscle might show interesting behaviors when twisting moments are applied.

Table 1. Anatomical data for the muscles used in the present study. The muscles shown are located in the right side of the body. Coordinates for the left side are obtained by reversing the sign of the Y coordinate. Positive X points laterally to the right, positive Y points anteriorly, and positive Z points upward. The origin of the coordinate system is the L3/L4 intervertebral space.

			Moment Arms (m)			Normalized Lines of Action		
Muscle	**Label**	**CSA (cm^2)**	*X*	*Y*	*Z*	*X*	*Y*	*Z*
Multifidus	MU	13.489	0.039	-0.051	-0.075	-0.328	-0.205	0.922
Longissimus Thoracis	LO	24.383	0.026	-0.058	-0.101	-0.002	-0.220	0.976
Iliocostalis	IL	19.487	0.069	-0.050	-0.074	-0.058	-0.105	0.993
Rectus Abdominis	RA	8.500	0.030	0.078	-0.198	0.132	0.020	0.991
External Oblique	EO	16.000	0.099	0.033	-0.059	0.209	-0.443	0.872
Internal Oblique	IO	19.500	0.122	0.022	-0.063	-0.618	0.579	0.531
Latissimus Dorsi	LD	8.000	0.024	-0.067	-0.034	0.347	0.183	0.920

Chapter 2. RESEARCH OBJECTIVES

2.1 Rationale for the study

As discussed in the previous chapter, back pain is a prevalent disease in our society. Not only is its frequency considerable, but treatment is expensive as well. Despite decades of extensive scientific study of the spine system, occupationally induced back diseases are still frequent. It can be argued that the scientific community has made little progress in gaining knowledge about the spine system with the necessary degree of applicability (Leamon, 1994). The number of muscles included in models has increased, the detail of the anatomy used has increased, and the number of parameters (e.g. vertebrae stiffness, ligament passive forces, vertebrae displacements) included has increased. Have those advances brought us any closer to understanding the mechanism of injury in that body region? Although some theories regarding injury mechanisms on the lumbar spine are available, we are really not much closer to confirming or disproving them than we were ten years ago. The question is, then, what needs to be done?

Even though they don't seem to have been completely successful so far, the predictive models described before may provide one piece of the puzzle. These models are needed due to the unavailability of practical (i.e. low cost, high ruggedness, and low intrusiveness) instruments to measure torso muscle recruitment patterns on the field. If we had this ability, and assuming spine compression (as calculated from the muscle recruitment patterns measured) is related to LBP, we could directly redesign the field tasks to reduce the risk of LBP. Since we don't have this ability, and it is unlikely we will have it in the near future, we need predictive models to produce realistic sets of muscle recruitment patterns that might occur in a given task. If we assume the models are a fair representation of these patterns, then the spine compression can be calculated, and the redesign process completed. The main limit on this approach is that some predictive models, it has been argued (Nussbaum, et al., 1997), may have reached a practical predictive limit with the use of current technology under static postures and loads. However, for this to be truly the case, predictive models have to be compared against EMG data obtained over a bigger range of loading magnitudes, loading directions (including axial twisting), and a larger number of subjects than the data currently available.

Even more importantly, intra- and inter- subject variability has to be measured and published. As difficult as the analysis of such variability may be, it is very possible that therein lies the link between biomechanics and epidemiology. If we are able to link particular groups of individuals that are different from the norm to low back disease, then we might be able to locate what aspects of or changes in behavior provoke injury. If an individual significantly changes their recruitment patterns from one trial to another, is it representative of random variation? Could that variation be caused by another mechanism? Can we accurately model these variations? Data is needed in order to answer these questions.

The weakest point of any of the models described before, and most biomechanical models for that matter, is the issue of model validation. Seldom can we take direct measurements of physiological processes in the human body. If this is the case, how can lumbar muscle recruitment models be validated? Two well thought out answers seem to be provided in Cholewicki and McGill (1996) and Hughes (1991). Cholewicki and McGill (1996) propose a validation approach that consists of component validation, internal validity checks, sensitivity analysis, and judgmental evaluation. Hughes (1991) proposes validation by subjecting a model to the greatest amount of testing possible. As the model continues to pass tests that it has a chance of failing, confidence in the model increases. If the model fails a test, reasons for this failure can be discovered and adjustments can be made.

ANN's, DMH, and SCI represent three recent and very different attempts to model human behavior. Based on the published data for each, they also appear to be well correlated with experimental EMG data. Nevertheless, a direct comparison between these models based on the published data may confound the results with other artifacts, such as the anatomy assumed. Therefore, the question whether one of these models is better remains to be answered. The importance of this comparison, especially when EMG data resulting from significantly different loading conditions is used, is that it provides for the indirect validation of the models. If the models pass tests with "flying colors", then confidence in the models increases. Models that fail tests can be studied for the cause of failure and improvements may result. In the long run (i.e. over several experiments), and as models evolve, we might come closer to finding a method that accurately models the actual body mechanisms responsible for lumbar muscle activation patterns.

In summary, this experiment attempts to increase the scientific body of knowledge on lumbar mechanics with three main contributions. First, EMG data was collected from several lumbar muscles using larger loading magnitudes than those generally reported in the literature. Second, EMG data was collected for the same set of lumbar muscles over biplanar loading conditions that include torsional moments, instead of just the usual sagittal and frontal moments. The data collected is used in the assessment of the relative performance (third contribution) of ANN, DMH and SCI models under different sets of loading conditions.

2.2 Research Question

The present work statistically tests a set of EMG data collected experimentally against the muscle activation patterns predicted by the models under various experimental loading conditions. The experimental question tested is:

> *Across all the loading conditions tested, across all participants, and across experimental replications, a single model, either ANN, DMH, or SCI, will emerge as the best predictor of lumbar muscular recruitment patterns as quantified using correspondence with the collected EMG data.*

Chapter 3. EXPERIMENTAL METHODS

3.1 Experimental Design

The research presented here consists of two different phases. The first phase involved human participants that statically resisted several loads applied to their upper torso. EMG data measured from several lumbar and abdominal muscle groups were collected. This data was used as inputs in the second phase of the research. This second stage involves the statistical comparison of model predictions against the actual EMG values, as well as comparisons between models in terms of their predictive ability.

3.1.1 Phase I: EMG Data Collection.

The first phase obtained EMG data from anterior and posterior torso muscles in human participants. The goal of this phase was to obtain muscle recruitment data to be used in the evaluation of the predictive models.

3.1.1.1 Participants. A total of 8 participants were selected from a University student population. None of the participants had a previous history of back pain, back injury, or other disorders that would prevent them from resisting torques applied to the torso. These conditions were self-reported in a pre-experimental health questionnaire, shown in Appendix B, which also recorded age and gender. Weight and height were recorded by the experimenter before the experimental protocol is started. To avoid the process of scaling the models to account for subject variation, only participants falling within a ±10% range of the 50th male height and weight percentiles were selected. Although accurate scaling models do exist (e.g. Nussbaum and Chaffin, 1996a), their use would introduce an additional and undesired confounding factor in the experimental process. The male height and weight are considered because the anatomical studies used in the models are based on the male anatomy. Therefore, all measures reported in those studies should approximate the 50th percentile (average) male physique. It is assumed here that women with the same height and weight measures will also be described by the anatomical measures used if they fall in the same height and weight range. The height and weight values required range from 173.9-177.3 cm and 75.3-81.7 kg, respectively (calculated from data reported by Gordon, Churchill, Clauser, Bradtmiller, McConville, Tebbets, and Walker, 1989;

and Kroemer, 1981). A summary of the biographical data collected from the participants is presented in Table 2.

Table 2. Participant's Data

Participant:	***Gender:***	***Weight (kg):***	***Height (cm):***	***Age:***	***L3/L4 Height (cm):***
1	M	77.27	173.0	21	125.5
2	M	80.45	173.5	29	125.0
3	F	75.45	174.5	25	129.0
4	M	75.91	173.0	24	121.5
5	M	81.82	173.0	26	125.0
6	F	76.82	174.0	27	122.0
7	F	75.91	177.0	28	123.0
8	F	81.00	175.0	24	126.0
Average (SD):	--	***78.08 (2.58)***	***174.13 (1.38)***	***25.50 (2.56)***	***124.63 (2.43)***

Participants started the experimental process after signing an informed consent form (see Appendix A), if they chose to participate. To protect the participants, the experimental protocol was approved by the Virginia Tech Institutional Review Board (IRB). Participants were monetarily compensated for their participation at a rate of $5.00/hr., and were free to withdraw from the study at any time without penalty.

3.1.1.2 Apparatus and Instrumentation. The participants performed the required exertions while standing. While completing the experimental trials, their feet were separated at about shoulder width, with both feet completely touching a force platform (Bertec). To prevent involuntary movement of the legs and pelvis during the exertions, the participant's ankles, knees, and pelvis were attached via straps to a rigid fixture bolted on top of the force plate. This approach has previously been used successfully in several studies (e.g. Granata, Marras and Fathallah, 1996; Raschke, 1994).

The participants resisted the moments applied through a shoulder harness. According to McMulkin, et al. (1998) and McMulkin (1996), this type of loading produces lower muscle activation levels than the use of hand-held loads. They concluded that the difference might be due to the activation of shoulder muscles in the hand-held situation. Since such activity was not monitored, the shoulder harness method was deemed preferable. Figure 6 sketches the experimental setup used, while Figure 7 illustrates the actual setup. The centerline of the harness went across the torso circumference at approximately the nipple level. The harness had load attachment points at the front (center of the chest), rear (over the spine), and sides (on a horizontal cable that crosses over each arm and is attached to the harness). This approach was also used in Lavender, et al. (1992a, 1992b). The distance from the strap's centerline to the L3/L4 interspinous process was measured as the load's moment arm for the sagittal and frontal moments. The distance from the strap's lateral attachment to its center was considered the moment arm for the horizontal plane moments.

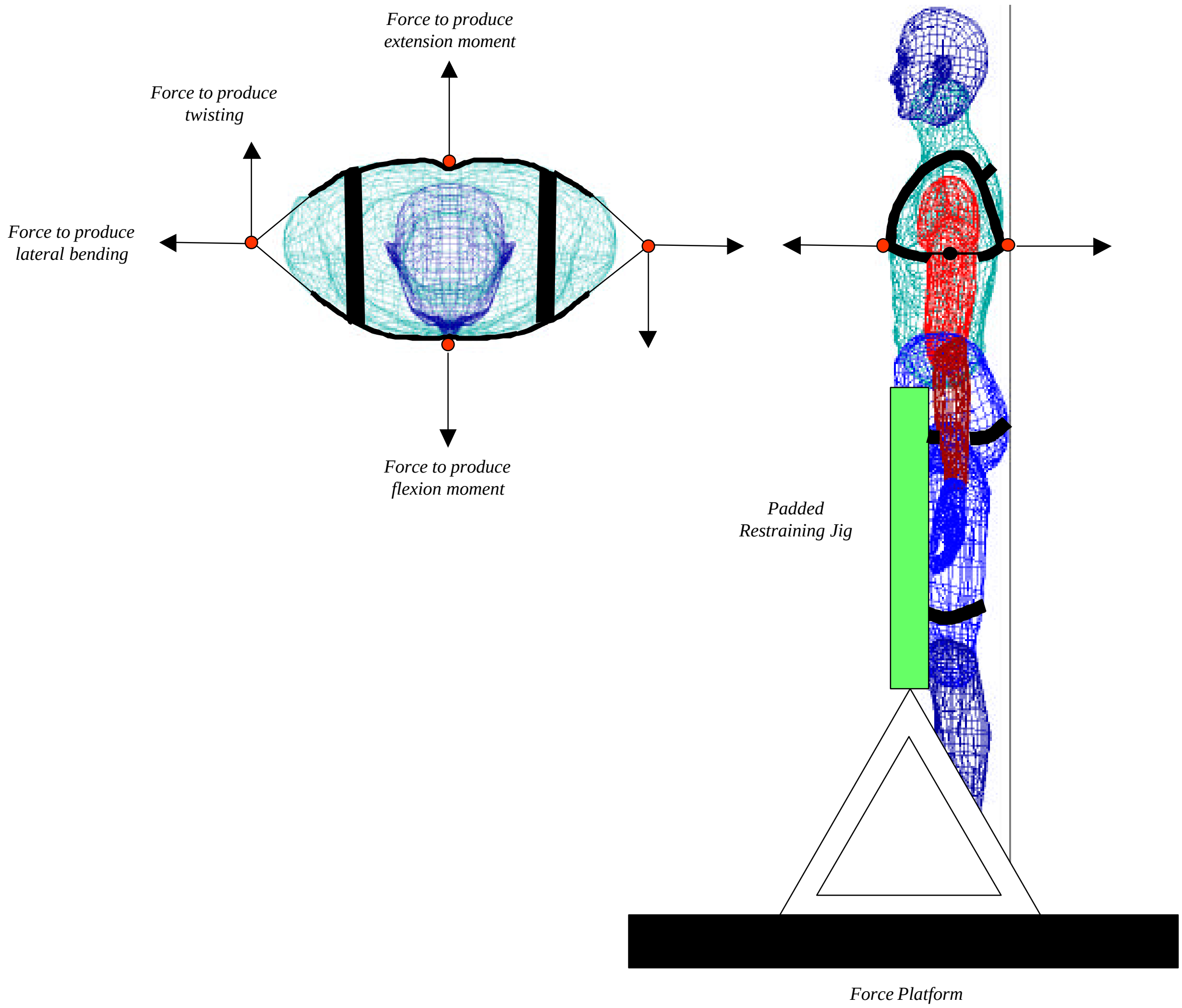

Figure 6. Experimental setup. Red circles are load attachment points. The forces will be generated through vertical loads redirected through pulleys and attached to the harness via cables.

Figure 7. Actual experimental setup.

Surface-EMG recordings were obtained from selected trunk muscles using bipolar disposable electrodes. Before placing the electrodes, the skin was lightly rubbed and cleansed with alcohol. The surface signals were transmitted through short (<30cm) leads to preamplifiers (100x gain). EMG signals were then hardware amplified, band-pass filtered (30-1000 Hz), RMS converted (100ms time constant), AD converted (512 Hz), and stored on disk.

3.1.1.3 Electrode Placement. Electrodes were placed over seven muscle pairs (a total of 14 electrode placement sites), as described by van Dieen (Personal Communication, August 1997) and Biedermann, et al. (1990) for the longissimus thoracis, iliocostalis lumborum and multifidus muscles; McGill (1992) and Lavender (1992a) for the rectus abdominis, internal oblique, and latissimus dorsi; and Kelaher, et al. (1995) and Cram, et al. (1998) for the external oblique. Table 3 indicates the muscle pairs, the acronym used for their identification, the orientation of the electrode (with respect to the horizontal) and the electrode location used.

3.1.1.4 Independent Variables. Data in this phase was collected using a 2X2X3X5 mixed factor design using 8 participants. The four independent variables were gender, load magnitude, load plane, and load orientation. Gender was the only between subject variable. Each participant represented a blocking variable. Each participant also performed two trials for each of the treatments. A total of 22 treatments, illustrated in Table 4, was performed to complete the experiment. The total is different from that suggested by the within subject independent variables (30) due to the duplication of several loading conditions. A description of the within subject independent variables and the procedure used for treatment ordering follows.

Table 3. Electrode placement

Muscle Pair	***Acronym***	***Orientation***	***Electrode Location***
Longissimus Thoracis	LO	90°	3 cm lateral of the L1 spinous process
Iliocostalis Lumborum	IL	Parallel to the line described in the next column	1 cm medial to a line from the ipsilateral posterior superior iliac spine to the lateral border of the iliocostalis at the twelfth rib at the level of the L2/L3 interspinous space.
Multifidus	MU	Parallel to the line described in the next column	Medially to a line from the ipsilateral posterior superior iliac spine to the L1-L2 insterspinous space at the L4-L5 interspinous space.
Rectus Abdominus	RA	90°	3 cm lateral to the umbilicus
External Oblique	EO	72°	Lateral to the Rectus Abdominus, directly above the anterior superior iliac spine, halfway between the iliac crest and the ribs.
Internal Oblique	IO	45°	Below EO dorsal electrode; superior to inguinal ligament
Latissimus Dorsi	LD	45°	~14 cm lateral to T9 spinous process over muscle belly

Load orientation. The direction was varied in five equally spaced steps between 0 and 180 degrees. This is an approach similar to the one used by Lavender, et al. (1992b), although they used seven equally spaced orientations in that range. For sagittal-frontal plane loading, 0° represents applied flexion, 90° represents right lateroflexion, and 180° represents applied extension. For sagittal-horizontal plane loading, 0° represents applied flexion, 90° represents counterclockwise twisting, and 180° represents extension. For frontal-horizontal plane loading, 0° represents counterclockwise twisting, 90° represents right lateroflexion, and 180° represents clockwise twisting.

Table 4. Experimental Treatments.

Treatment	Load Magnitude (% MVE)	Load Plane	Load Orientation
1	50%	Sagittal-frontal	0°
2	50%	Sagittal-frontal	45°
3	50%	Sagittal-frontal	90°
4	50%	Sagittal-frontal	135°
5	50%	Sagittal-frontal	180°
6	90%	Sagittal-frontal	0°
7	90%	Sagittal-frontal	45°
8	90%	Sagittal-frontal	90°
9	90%	Sagittal-frontal	135°
10	90%	Sagittal-frontal	180°
11	50%	Sagittal-horizontal	45°
12	50%	Sagittal-horizontal	90°
13	50%	Sagittal-horizontal	135°
14	90%	Sagittal-horizontal	45°
15	90%	Sagittal-horizontal	90°
16	90%	Sagittal-horizontal	135°
17	50%	Frontal-horizontal	45°
18	50%	Frontal-horizontal	135°
19	50%	Frontal-horizontal	180°
20	90%	Frontal-horizontal	45°
21	90%	Frontal-horizontal	135°
22	90%	Frontal-horizontal	180°

Load magnitude. Load magnitude was varied as a percentage of the vector combination of the MVE's each participant was able to generate at each particular load direction. Figure 8 shows the interpolation method used for determining biplanar strengths from the uniplanar MVE's collected (the sagittal-frontal planes are considered in the figure). The axes are scaled in such a way that the participant's uniplanar MVE's are equidistant from the origin. The concentric circles indicate the combination of uniplanar loads that will approximate the intended load at any specific orientation (e.g. the outer circle indicates 90% MVE). A specific load orientation is shown for 45°. For any combination involving the sagittal plane, in which flexion and extension moments are not resisted by the same set of muscles (as opposed to right vs. left twist, or right vs. left lateral moments), the loads for flexion and extension loads were calculated from the appropriate efforts (i.e. flexion or extension). The levels of this factor will be 50% and 90% of each participant's MVE's.

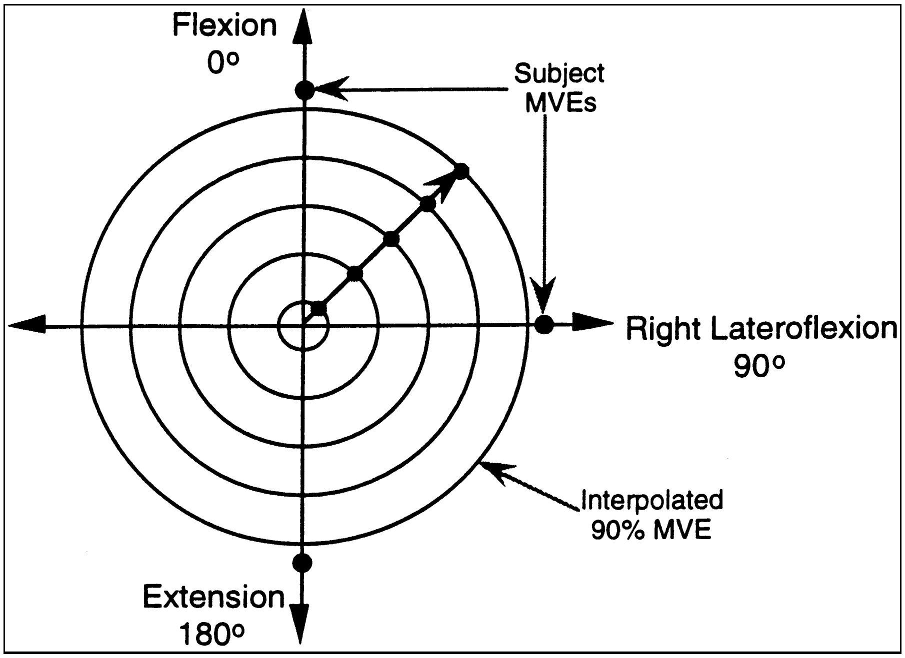

Figure 8. MVE interpolation method

Load plane. Three different load planes were used. These include sagittal-frontal, sagittal-horizontal, and frontal-horizontal. The loading planes were varied by changing the load's attachments to the harness (as shown in Figure 6). Sagittal moments were produced by attaching loads to the anterior or posterior sections of the harness, in a direction perpendicular to the harness. Frontal moments were produced by attaching loads to the sides of the harness, in a direction perpendicular to the harness. Horizontal moments were produced by attaching loads to the sides of the harness, in a direction parallel to the harness. Furthermore, horizontal moments were produced by using coupled forces (i.e. forces acting on opposite directions on opposite sides of the body). This eliminated the production of moments in any other plane by the forces used to produce the horizontal moment.

Order of treatments. Whenever a within subjects variable is used, it is possible that participants may learn to perform the experimental task better (e.g. reduced muscular activation levels) as the experiment progresses. Although there's limited evidence as to the contrary

(Nussbaum and Chaffin, 1997, consistent muscle behavior over two experiments; and Chaffin, et al., 1998, consistent muscle behavior over repeated trial performance), learning effects should still be accounted for if possible. Learning might introduce an effect in performance that the experimenter cannot control or quantify, and which usually differs between subjects. To address this issue in this particular experiment, each participant will receive a treatment order determined at random, but different from the other participants. Thus, sixteen different treatment orders, one for each participant, have been generated using the random function in the SAS statistical programming language. Table 5 illustrates the 8 orders generated, please refer to Table 4 for a description of the treatments. To further reduce any effects of learning, enough practice trials to familiarize the participant with the experimental protocol were performed. This was intended to stabilize any learning process before the experimental trials were started. Trial repetitions were completed on the reverse order shown in Table 5 (i.e. the last treatment suggested on the table was performed first).

Table 5. Random treatment orders

	SUBJECTS							
Order	**S1**	**S2**	**S3**	**S4**	**S5**	**S6**	**S7**	**S8**
1	22	19	2	7	16	4	1	4
2	16	3	16	10	14	15	11	10
3	10	20	18	22	11	20	6	21
4	8	7	3	1	1	18	18	11
5	11	10	1	17	9	22	9	7
6	14	9	11	4	6	12	5	18
7	7	18	14	9	8	13	12	12
8	9	6	22	13	20	8	19	16
9	21	8	21	15	10	6	14	19
10	20	22	7	18	3	14	2	6
11	4	1	9	6	12	16	4	22
12	17	14	20	3	5	21	3	20
13	2	15	8	2	17	5	7	13
14	15	16	15	19	4	11	16	2
15	1	4	4	5	7	7	15	9
16	6	17	6	14	18	1	8	5
17	18	12	5	8	15	3	20	15
18	5	13	12	11	22	17	21	3
19	19	5	19	12	2	10	22	17
20	13	11	17	20	13	9	10	1
21	12	21	13	16	21	2	17	14
22	3	2	10	21	19	19	13	8

3.1.1.5 Dependent Variables. The main dependent variable in this phase is the EMG data for each of the sampled muscle pairs. Although it is generally accepted that this measure does correlate to muscle force generation, researchers disagree on the type of relationship (Redfern, 1992). Some researchers report the relationship as linear in several muscle groups for static efforts (Perry and Bekey, 1981; Hof and Van Den Berg, 1977; Stokes, et al., 1987). Others report the relationship as curvilinear (Lawrence and DeLuca, 1983; Stokes, et al., 1989). Hatze (1980) for example, has warned against the use of EMG for validation of force predictions, especially during dynamic activities, because the relationship between EMG and muscle force in dynamic activities is poorly understood.

In any event, only the limited assumption of a monotonic relationship between EMG and force is required here, given the static exertions and unchanging postures (Hughes, 1991). Please refer to section 3.1.1.7 for further discussion on this dependent variable.

The second dependent variable collected here is the forces and moments transmitted to the force platform. This variable will be used to corroborate that the experimental loads were transmitted properly to the participant.

3.1.1.6 Experimental Procedures. Upon their arrival, the participants' height and weight were measured. The experimenter then proceeded only if the participant's height fell within a ±10% range of the mean population height and weight. The participants then read the informed consent form (see Appendix A) and signed it if they agreed to participate in the experiment. They then completed a pre-experimental health questionnaire (see Appendix B). After the questionnaire was completed, participants were given descriptions of the efforts required. They were placed on the experimental apparatus and practiced MVE's. After doing so, they were instructed to perform preliminary MVE's for determination of the load magnitudes to be used in the experimental conditions. After performing these exertions, a future time was set for completion of the remainder of the experiment. The first session of the experiment took an average of 45 minutes per participant.

After this first session was completed, the participant arrived to the next session, and the electrodes had been placed on the participant, the experimenter instructed the participant on the next part of the experiment, performance of maximum voluntary exertions, which was somewhat different from those collected in the first day. MVEs performed are adapted from those described by McGill (1991) and McGill (1992). The tests are:

(1) A standard sit-up with additional manual resistance provided by one of the experimenters (trunk angle with horizontal approximately 30°).

(2) Participants, leaning over the edge of a test bench with their legs restrained. While laying on the back supine, an isometric flexor efforts are performed with or without twisting (three different efforts); and laying on the stomach prone, an extensor effort. All these efforts were resisted by the experimenters.

(3) Maximum isometric exertions while standing in the restraint jig described in the apparatus section. This category includes flexor, lateral bend (left and right), extensor, and isometric twist (clockwise and counterclockwise) efforts, with the resistance provided by the shoulder harness, whose respective attachment points were fixed.

(4) While the participant is standing on the jig, without the harness in place, attempted shoulder abduction.

The first and second exertions were used to set the EMG amplifier gains, and no data was collected from them. For any particular muscle, 100% MVE will be the maximum activity observed during any of the third and fourth MVE strategies. Two trials of each exertion (of the third and fourth types) were performed, both before starting the experimental session. Trials of the first and second exertions were performed as many times as necessary to set the gains. Section 3.1.1.7 explores the EMG data transformation process that makes use of the MVE data.

The maximum torque generated in the extensor, lateral to the left, and flexor efforts in the first day was used for determination of the actual loads to use in the different levels of the load magnitude dependent variable. As mentioned before, each MVE effort was performed twice (on both days), with each individual exertion lasting from 4 to 6 seconds and including periods of ramp-up, peak, and ramp-down (Chaffin and Andersson, 1991). Exertions not exhibiting these characteristics were not used and were repeated, after appropriate resting time was provided.

After the MVE's were complete, as well as after each treatment, the experimenter let the participant rest for a minimum of two minutes, to reduce the effects of fatigue in the experimental trials. This time period is in the range suggested by Chaffin and Andersson (1991). The participant was encouraged to rest for longer periods if they felt it was necessary. During the period the participant was resting, the experimenter set-up the next experimental trial. At all times, except when instructed otherwise by the experimenter, the participant remained standing, strapped to the jig in the force platform.

All straps and the shoulder harness were as tight as possible without producing discomfort in the participant. The experimenter instructed the participant to report any discomfort of any kind immediately.

Before the participant was strapped into the jig, he/she was asked to lie down, face up, on a padded bench. For a period of four seconds after the participant complied, the experimenter captured EMG data. The data collected in this stage was used later to determine a resting EMG value for each muscle.

The experimental treatments proceeded in the order determined by the randomization process for each participant. For each trial, EMG data was collected for at least two seconds on each trial after the participant had stabilized his/her posture under the load. To maintain consistent postures throughout the experiment, the participant was asked to maintain torso contact with appropriately placed bungee cord lines when performing an exertion, with as minimum stretching of the lines as possible. Three lines were adjusted to lightly touch the participants when they were in a neutral (i.e. standing straight) posture, one in front of the participant and one on each side. The lines were on the participant's line of sight.

Once the first pass through the experimental conditions was over (see Table 5) a second pass was performed. The order of the treatments for the second pass was the reverse of that used in the first one. Once the experimental treatments were over, the experimenter thanked the participant for their time and effort and paid them the amount of money they had earned. The second experimental session lasted an average of 4 hours per participant.

3.1.1.7 EMG Data Processing. At this stage, all EMG signals (i.e. Volts vs. time) were available. The EMG data processing effort uses the root mean square (RMS) transformation. The result of this transformation is a measure of the electrical power in the signal (LeVeau and Andersson, 1992). Some researchers suggest that this transformation appears to have a linear relationship with tension for brief isometric contractions (LeVeau and Andersson, 1992), although, as discussed before, this is still an arguable statement. The RMS processed EMG signal was collected over a two-second window in which the participant is stable while resisting the applied load. One second of the data collected over this window was then averaged. The actual second of data that was selected for averaging was determined by the experimenter upon visual observation of the data, to ensure that it was as stable as possible (i.e. small fluctuations in values). An analogous process was performed for the MVE's and the resting EMG measures. However, only the peak sections of the EMG spectrum for the MVE's were used. These transformed data were combined into a resulting value using equation 10.

$$NEMG_i = \frac{test\_value_i - resting\_value}{MVE\_value - resting\_value} \qquad (10)$$

where i indexes each of the 14 muscles, $test\_value_i$ are the processed EMG data from the experimental trials, *MVE_value* represents the processed EMG data for the MVE trials, and *resting_value* represents the EMG data gathered with the participant restrained on the jig. The result, NEMG, is the normalized EMG signal, and represents the degree of average muscle activation as a proportion of the maximum voluntary activation. This approach was used by Seroussi and Pope (1987) to study trunk muscle response to the application of static moments (see also Mirka, 1991, for a broader discussion).

Once the EMG data was normalized, the resultant set of moments they would theoretically generate was calculated, using the following formula:

$$\mathbf{M}_{\mathbf{L3/L4}} = \sum_{j=1}^{m} (g * pcsa_j * act_j) * t_j \times \mathbf{r}_j \qquad (11)$$

where g is the muscle's gain (i.e. force generated per unit of area), act_j is the activation of muscle j, $\mathbf{M}_{\mathbf{L3/L4}}$ is the three dimensional joint torque, $pcsa_j$ is the physiological cross sectional area of muscle j, $\boldsymbol{t}_j$ represents the direction of the muscle's line of action, $\mathbf{r}_j$ is the moment arm of the muscle with respect to the L3/L4 center of vertebral rotation, and m is the number of muscles used in the model. The calculation of the moment at L3/L4 is necessary to study the agreement of the EMG data collected with the set of moments measured in the force plate. Theoretically, both moment calculations should closely agree if the parameters shown in equation 11 are selected properly.

A note on muscle gain (g) is necessary at this point. This parameter has been estimated for different muscles under different conditions, and researchers disagree on an appropriate value that encompasses all muscles. However, most researchers agree that values falling in the range of 30-100 N/cm^2 appear physiologically valid. In the selection of a value for this criterion in this work, the sources presented in Table 6 were consulted.

Table 6. Gain values proposed in the literature

Reference	***Force/area (N/cm ^{2}):***
McGill and Norman (1987)	30.0-90.0
Morris, et al. (1968)	39.2
Ikai and Fukunaga (1968) (as cited in McGill and Norman, 1987)	63.0
Farfan (1973) (as cited in McGill and Norman, 1987)	34.3-82.3
Weis-Fogh and Alexander (1977) (as cited in McGill and Norman, 1987)	30.0
Schultz, et al. (1982)	100.0
Granata and Marras (1993)	30.0-100.0
Bogduk, et al. (1992)	46.0
Narici, et al. (1988)	70.5-80.1
Narici, et al. (1992)	25.0

Based on the values found in the literature for this parameter, a range of 25-100 N/cm^2 was deemed acceptable. The gain used for the generation of muscle forces (from the EMG data) was then determined by minimizing the sum-of-squares difference between the L3/L4 moment predicted by the EMG data and the L3/L4 moment determined from the force plate data. The value that minimized the average error was near 30 N/cm^2. This is the value used in the rest of this work. While a gain value could be calculated for each participant, for sets of muscles (Nussbaum and Chaffin, 1998), or even for each individual muscle, it is not appropriate to do so in this work, since the predictive ability of the models would be directly dependent on a parameter calculated from individuals' data.

3.1.1.8 Force Plate Data Processing. Data collected from the force plate consisted of the forces and moments applied on it. To transform this data into suitable inputs to the models, a modification of the technique suggested by Granata, et al. (1996) was employed. Instead of utilizing the moments at the force plate as a starting point (i.e. a bottom-up approach), the applied forces were used as the starting point (i.e. a top-down approach). This approach was employed because it is computationally easier than the Granata, et al. (1996) approach, which for the current experiment would have required the determination of the instantaneous center of pressure at the surface of the force plate. The calculation of the center of pressure would have been required because the disagreement between forces and moments collected is arguably the result of vertical forces that were not directed through the center of the force plate. Thus, these forces caused a reaction moment in the force plate that affected the moment data collected. The moment arms through which these vertical forces acted would have to be calculated using the center of pressure approach requiring further computations, and, thus, the top-down approach was employed. Equations 12,13, and 14 show the manipulation described here mathematically.

$$\mathbf{M}_{\mathbf{L3/L4(x)}} = F_{FP(y)} * (SH - L3/L4) \qquad (12)$$

$$\mathbf{M}_{\mathbf{L3/L4(y)}} = F_{FP(x)} * (SH - L3/L4) \qquad (13)$$

$$\mathbf{M}_{\mathbf{L3/L4(z)}} = M_{FP(z)}) \qquad (14)$$

where,

$\mathbf{M}_{\mathbf{L3/L4()}}$	estimated moment at the L3/L4 joint
$F_{FP()}$	measured force at the force plate
SH	measured strap height
L3/L4	measured height of L3/L4 (assumed at iliac crest level)

3.1.2 Phase II: Model Evaluation.

The second phase compared lumbar muscle recruitment patterns predicted by the ANN, DMH, and SCI models against those that can be inferred from the surface EMG collected during Phase I of the experiment. To reduce confounding effects, each model used, to the extent they required it, the same geometric database described in Table 1. Each model was tested as close as possible to its published form (e.g. similar parameters to those published were chosen).

3.1.2.1 Simulation procedure. All models were prepared for pattern generation as necessary. Moments at the L3/L4 disc (determined from Phase I) were then used as inputs for each of the models. Each of the models then produced muscle activation patterns for each of the moments inputted. These were translated, as necessary, into activation patterns (percent of maximum) by dividing the predicted muscle force over the muscle's cross-sectional area and the maximum stress level (30 N/cm^2). Thus, for each model, 4928 (14 muscles X 11 loading orientations X 2 loading magnitudes X 2 repetitions X 8 participants) output values were obtained.

Chapter 4. RESULTS

4.1 Phase I: EMG Data Collection

The first phase obtained EMG data from anterior and posterior torso muscles in human participants. The goal of this phase was to obtain muscle recruitment data to be used in the evaluation of the predictive models.

In this phase of the experiment, NEMG values were the main dependent variable. An ANOVA analysis was performed on the NEMG values considering the following factors and all their interactions: gender, load magnitude, load direction, muscle, and task repetition, where gender is the only between subject factor. The resulting ANOVA table is presented in Table 7. The load direction factor is the combination of the load direction and load plane factors discussed previously. Recall that the experimental design allowed the elimination of certain data points that were duplicated, resulting in 22 trials (11 loading directions X 2 magnitudes). For the rest of this document, these 11 loading directions are considered one factor (with eleven elements) and separated from the loading magnitude factor.

As expected, the main effects of and interactions between load magnitude, load direction, and muscle were significant at $\alpha = 0.05$. Gender and repetition, as well as their two-way interactions with other factors, were not significant. The only interaction in which Gender becomes significant is the four-way interaction Magnitude*Direction*Muscle*Gender, and any explanation of its significance is not attempted here. The interaction of Repetition*Gender, although not significant, is close enough to being significant to merit attention. Upon further examination, the almost-significant interaction is the result of a larger difference between male and female average activation levels during the first repetition than during the second repetition. This finding cannot be explained physiologically without the significance of any of the main effects involved. The non-significance of Repetition and its interactions indicates that intra-subject differences are undetectable, and, thus, repetition data are pooled from this point on.

Graphs of the average activation patterns per muscle and loading condition are presented in Figures 9 to 19. Each graph contains the activation pattern for the 50% load and the 90% load. The line representing the 50% magnitude also includes error bars that indicate one standard deviation of the sample (inter-subject differences). The graphic accompanying each figure indicated the loads applied to the participant.

Table 7. ANOVA for NEMG

Source	DF	SS	MS	F	P
Between Subject					
Gender	1	1.952	1.952	0.280	0.614
Subject(Gender)	6	41.515	6.919		
Within Subject					
Magnitude	1	4.797	4.797	82.600	0.000 *
Magnitude*Gender	1	0.044	0.044	0.750	0.420
Magnitude*Subject(Gender)	6	0.348	0.058		
Direction	10	21.884	2.188	14.870	0.000 *
Direction*Gender	10	0.363	0.036	0.250	0.990
Direction*Subject(Gender)	60	8.833	0.147		
Muscle	13	21.723	1.671	4.480	0.000 *
Muscle*Gender	13	4.153	0.320	0.860	0.601
Muscle*Subject(Gender)	78	29.096	0.373		
Repetition	1	0.069	0.069	0.610	0.466
Repetition*Gender	1	0.583	0.583	5.100	0.065
Repetition*Subject(Gender)	6	0.686	0.114		
Magnitude*Direction	10	1.487	0.149	3.500	0.001 *
Magnitude*Direction*Gender	10	0.407	0.041	0.960	0.490
Magnitude*Direction*Subject(Gender)	60	2.552	0.043		
Magnitude*Muscle	13	0.442	0.034	2.230	0.016 *
Magnitude*Muscle*Gender	13	0.165	0.013	0.830	0.627
Magnitude*Muscle*Subject(Gender)	78	1.192	0.015		
Magnitude*Repetition	1	0.006	0.006	0.280	0.614
Magnitude*Repetition*Gender	1	0.001	0.001	0.040	0.840
Magnitude*Repetition*Subject(Gender)	6	0.131	0.022		
Direction*Muscle	130	34.671	0.267	9.270	0.000 *
Direction*Muscle*Gender	130	3.930	0.030	1.050	0.344
Direction*Muscle*Subject(Gender)	780	22.445	0.029		
Direction*Repetition	10	0.253	0.025	0.430	0.924
Direction*Repetition*Gender	10	0.650	0.065	1.120	0.365
Direction*Repetition*Subject(Gender)	60	3.491	0.058		
Repetition*Muscle	13	0.355	0.027	0.900	0.560
Repetition*Muscle*Gender	13	0.416	0.032	1.050	0.416
Repetition*Muscle*Subject(Gender)	78	2.378	0.031		
Magnitude*Direction*Muscle	130	3.454	0.027	3.400	0.000 *
Magnitude*Direction*Muscle*Gender	130	1.379	0.011	1.360	0.008 *
Magnitude*Direction*Muscle*Subject(Gender)	780	6.098	0.008		
Magnitude*Direction*Repetition	10	0.650	0.065	1.280	0.260
Magnitude*Direction*Repetition*Gender	10	0.647	0.065	1.280	0.263
Magnitude*Direction*Repetition*Subject(Gender)	60	3.037	0.051		
Direction*Repetition*Muscle	130	1.303	0.010	0.780	0.959
Direction*Repetition*Muscle*Gender	130	1.541	0.012	0.930	0.706
Direction*Repetition*Muscle*Subject(Gender)	780	9.992	0.013		
Magnitude*Repetition*Muscle	13	0.063	0.005	0.800	0.661
Magnitude*Repetition*Muscle*Gender	13	0.086	0.007	1.090	0.380
Magnitude*Repetition*Muscle*Subject(Gender)	78	0.474	0.006		
Magnitude*Direction*Repetition*Muscle	130	0.796	0.006	0.920	0.733
Magnitude*Direction*Repetition*Muscle*Gender	130	0.799	0.006	0.920	0.723
Magnitude*Direction*Repetition*Muscle*Subject(Gender)	780	5.216	0.007		
Total	4927	246.549			

(*) denotes significance at a = 0.05

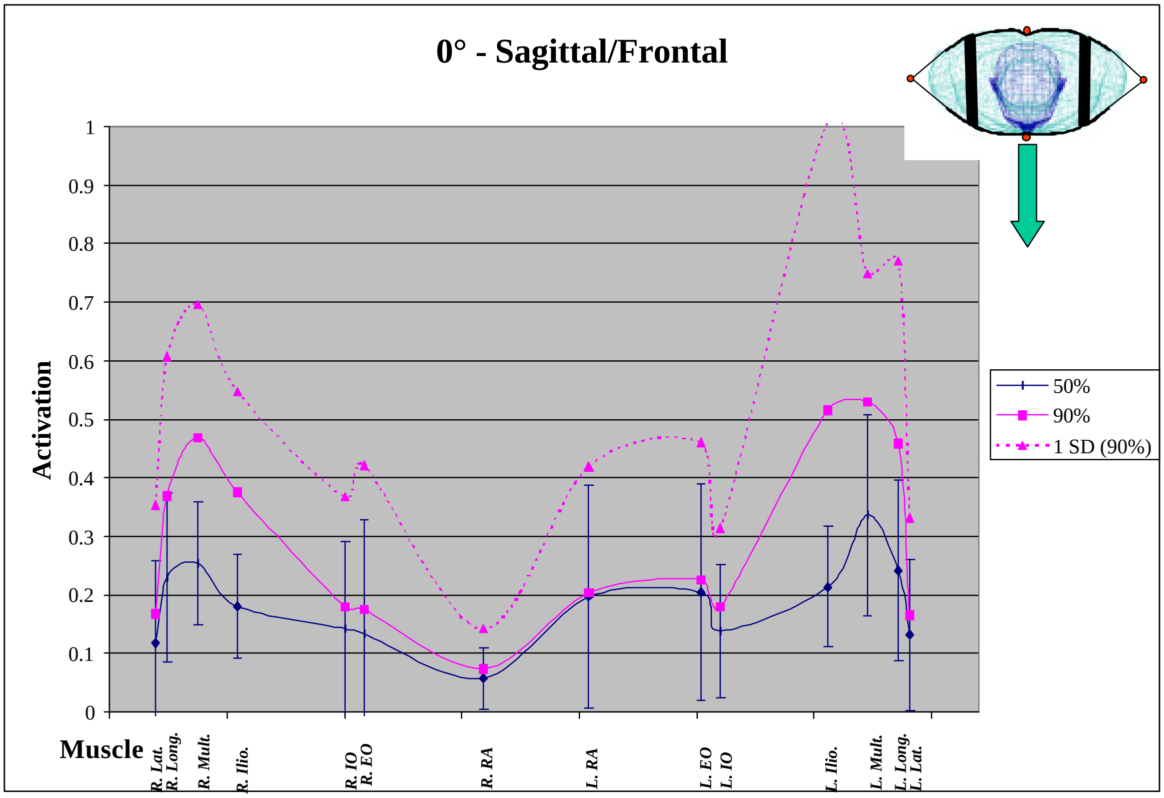

Figure 9. Muscle activation pattern for applied flexion

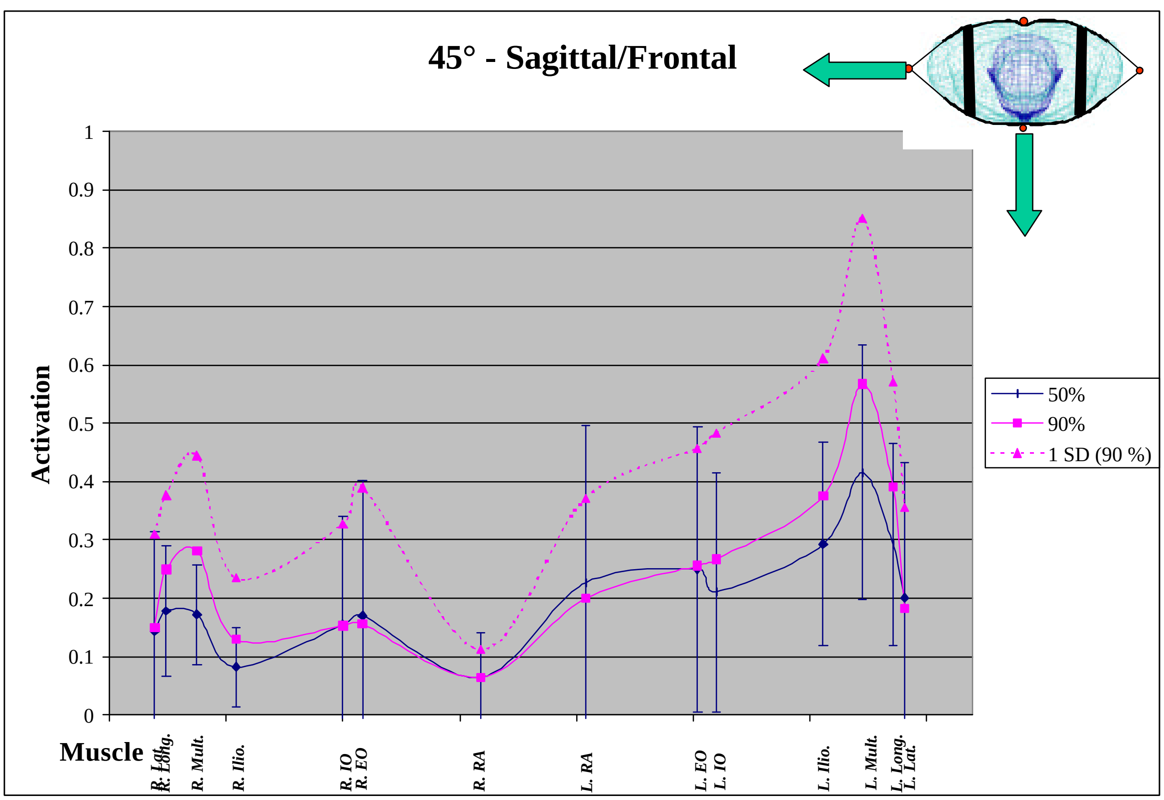

Figure 10. Muscle activation pattern for applied flexion and lateral bending

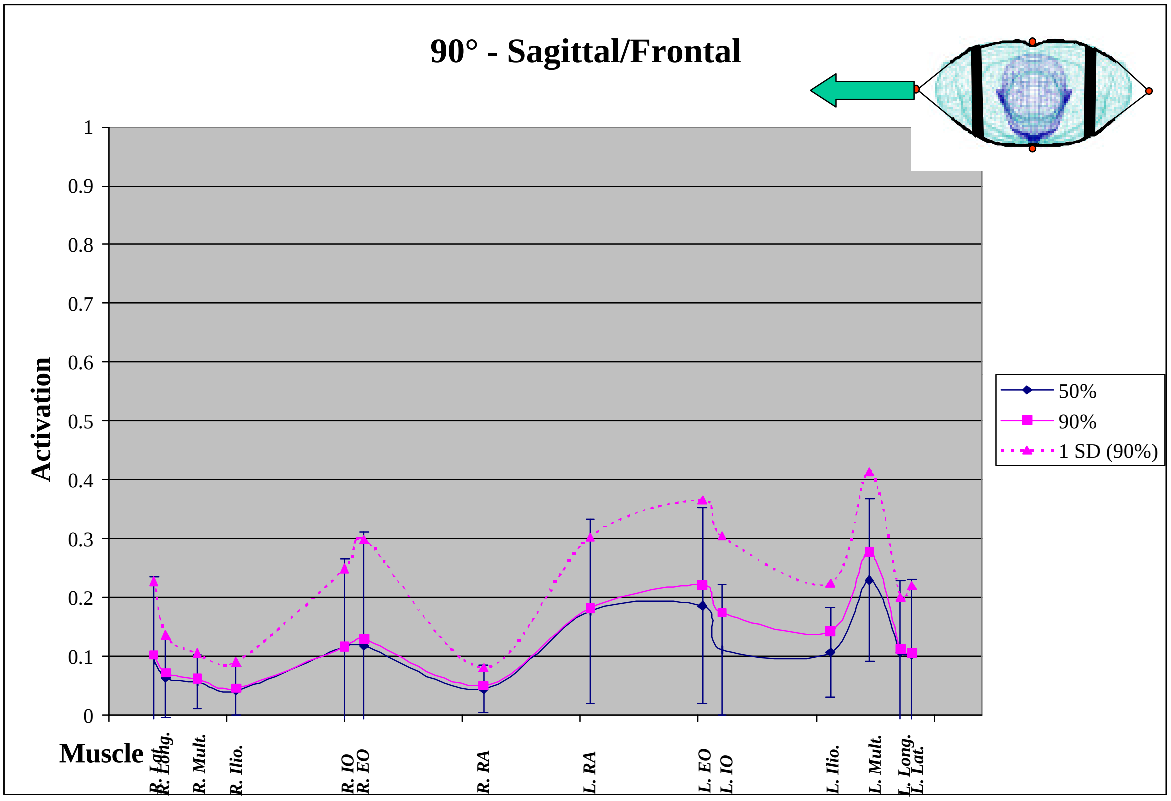

Figure 11. Muscle activation pattern for applied lateral bending

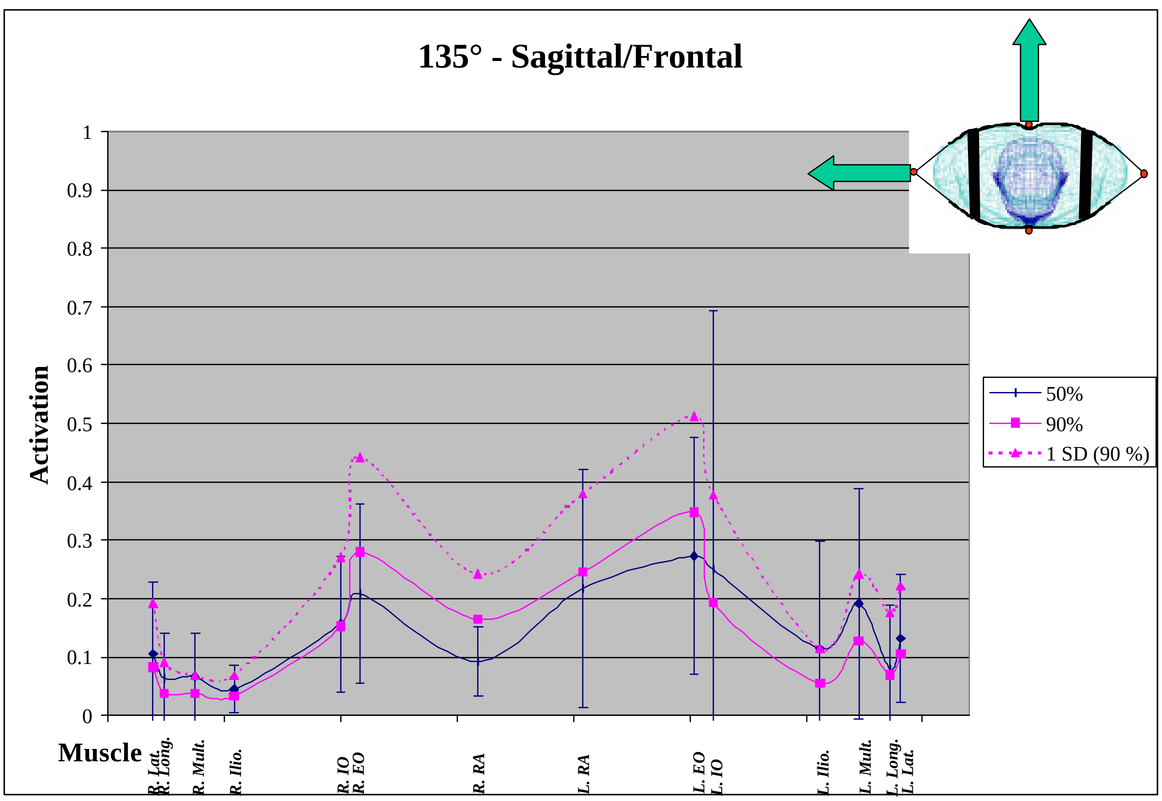

Figure 12. Muscle activation pattern for applied extension and lateral bending

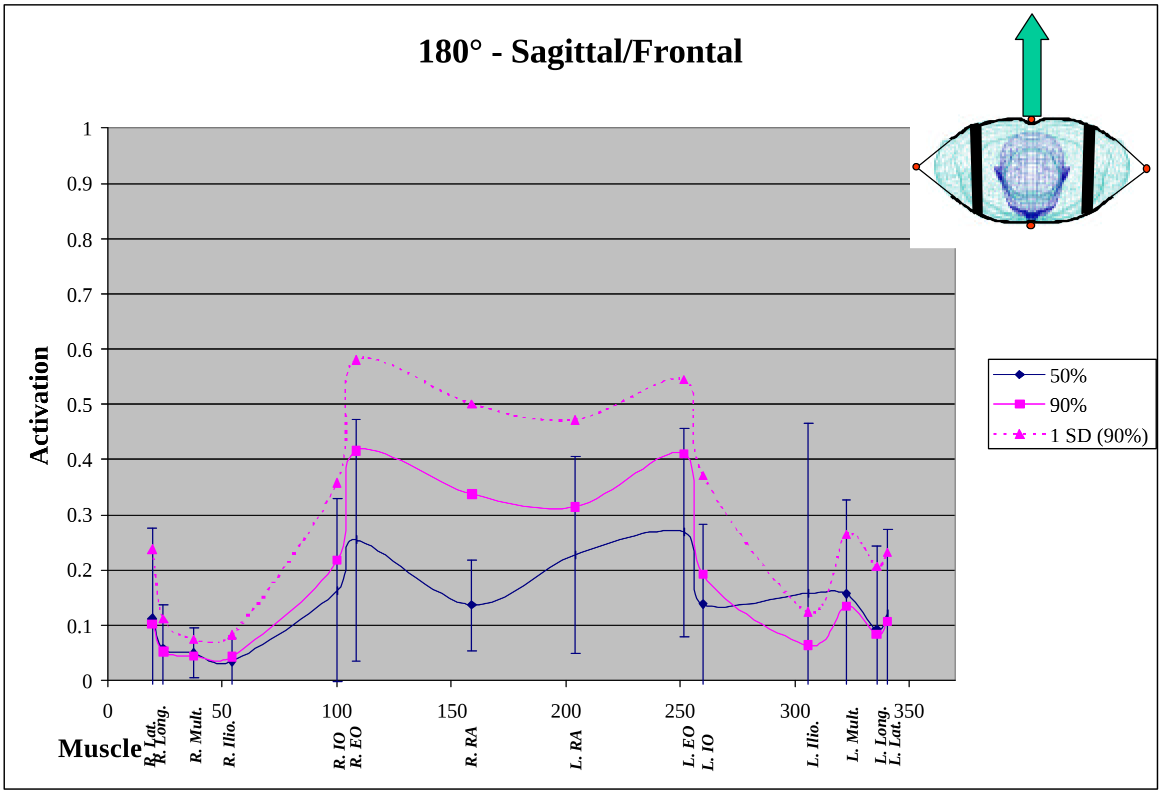

Figure 13. Muscle activation pattern for applied extension

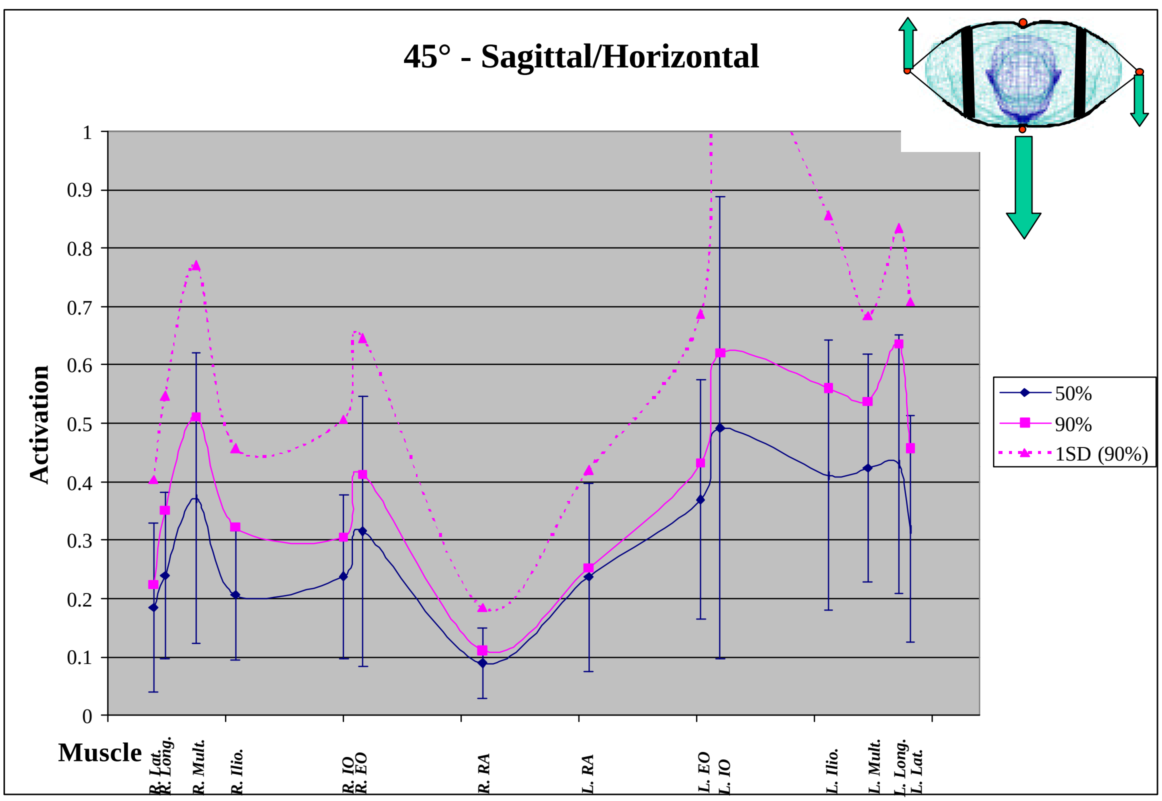

Figure 14. Muscle activation pattern for applied flexion and clockwise twisting

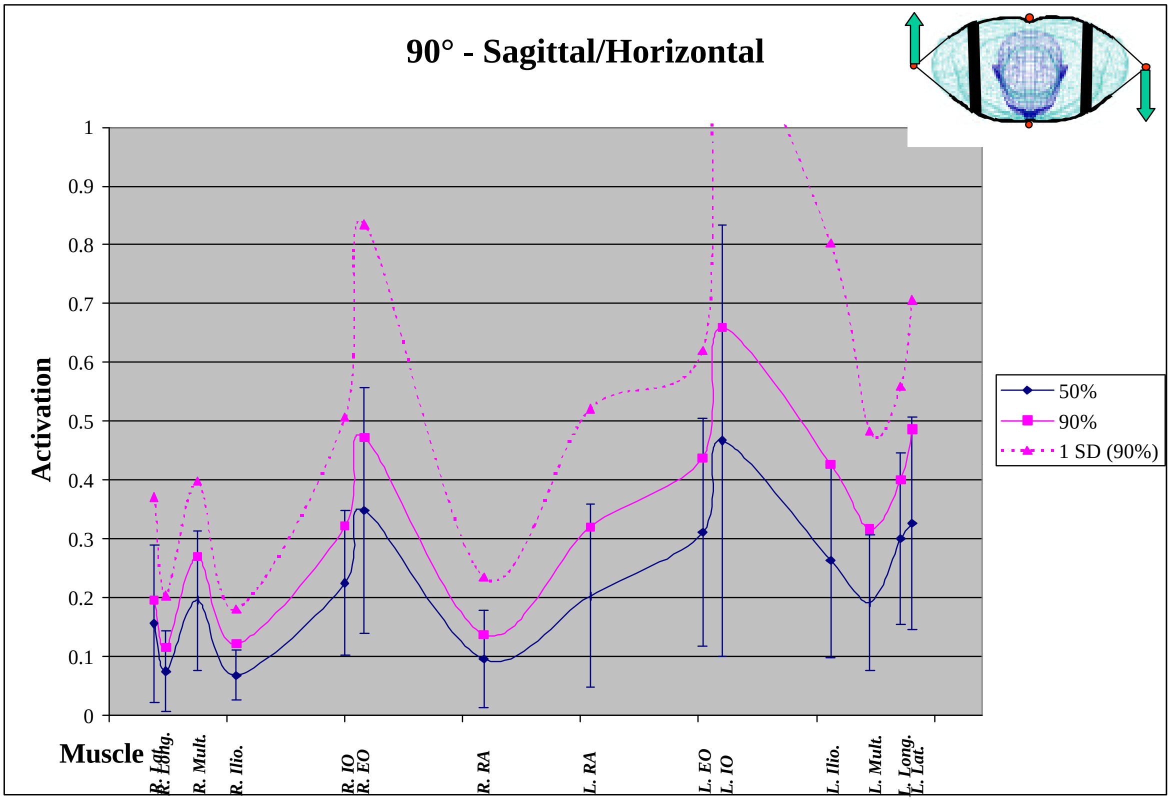

Figure 15. Muscle activation pattern for applied clockwise twisting

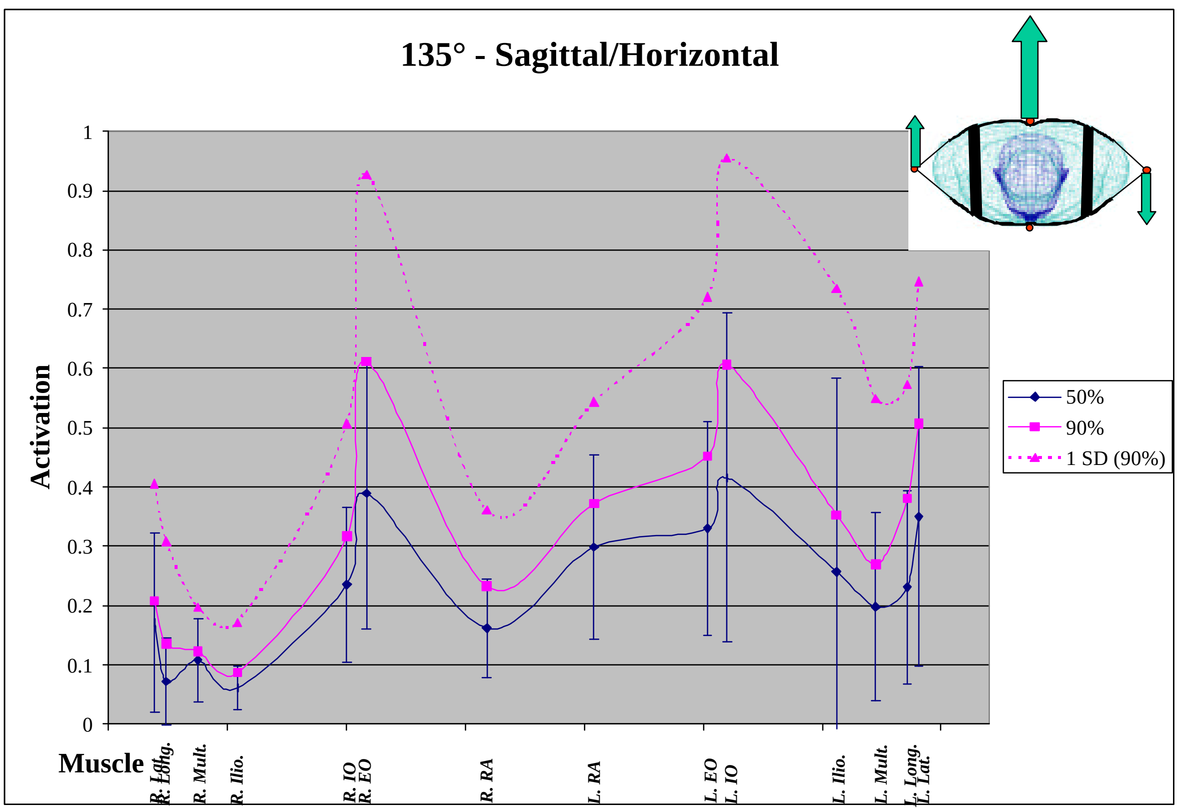

Figure 16. Muscle activation pattern for applied extension and clockwise twisting

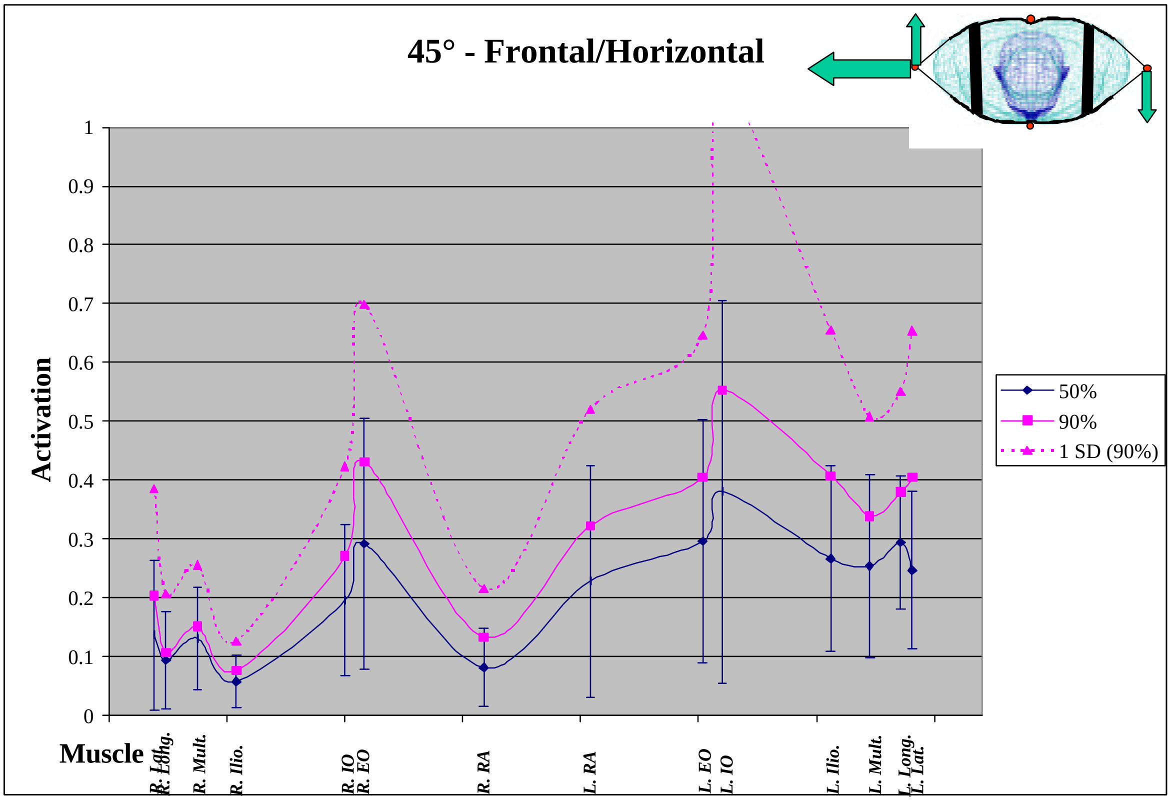

Figure 17. Muscle activation pattern for applied lateral bending and clockwise twisting

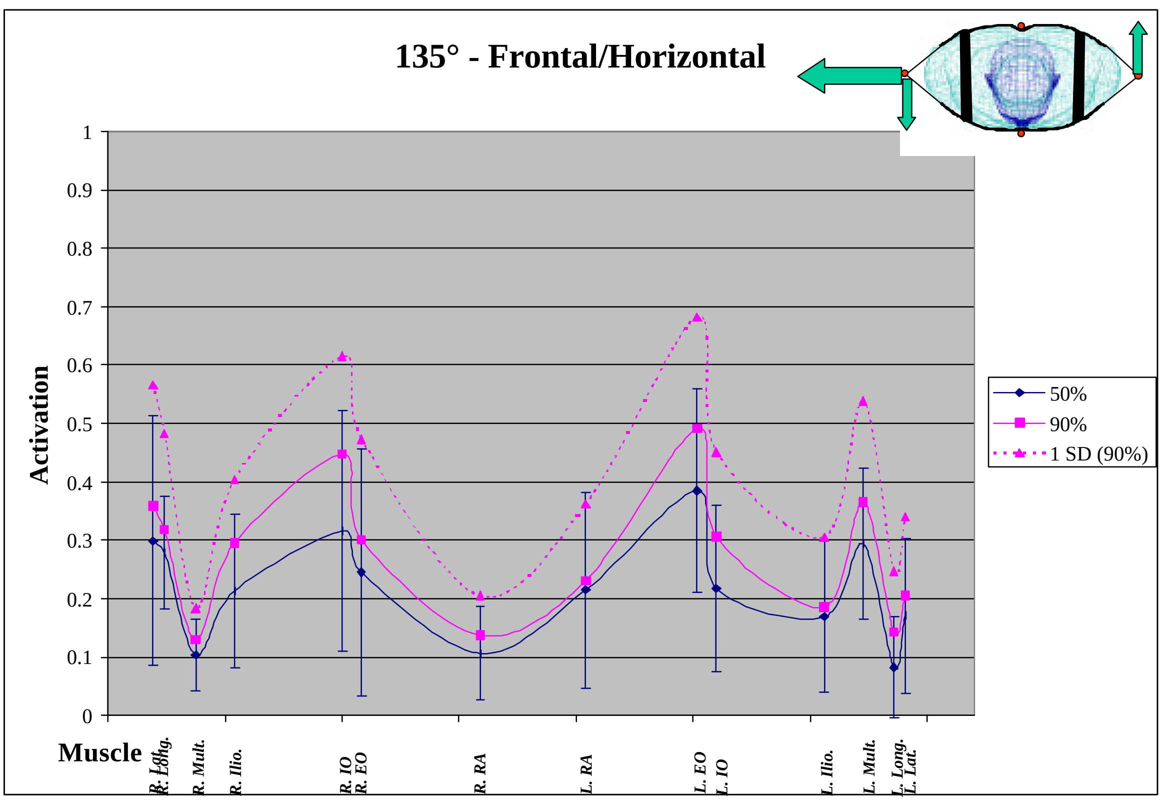

Figure 18. Muscle activation pattern for applied lateral bending and counterclockwise twisting

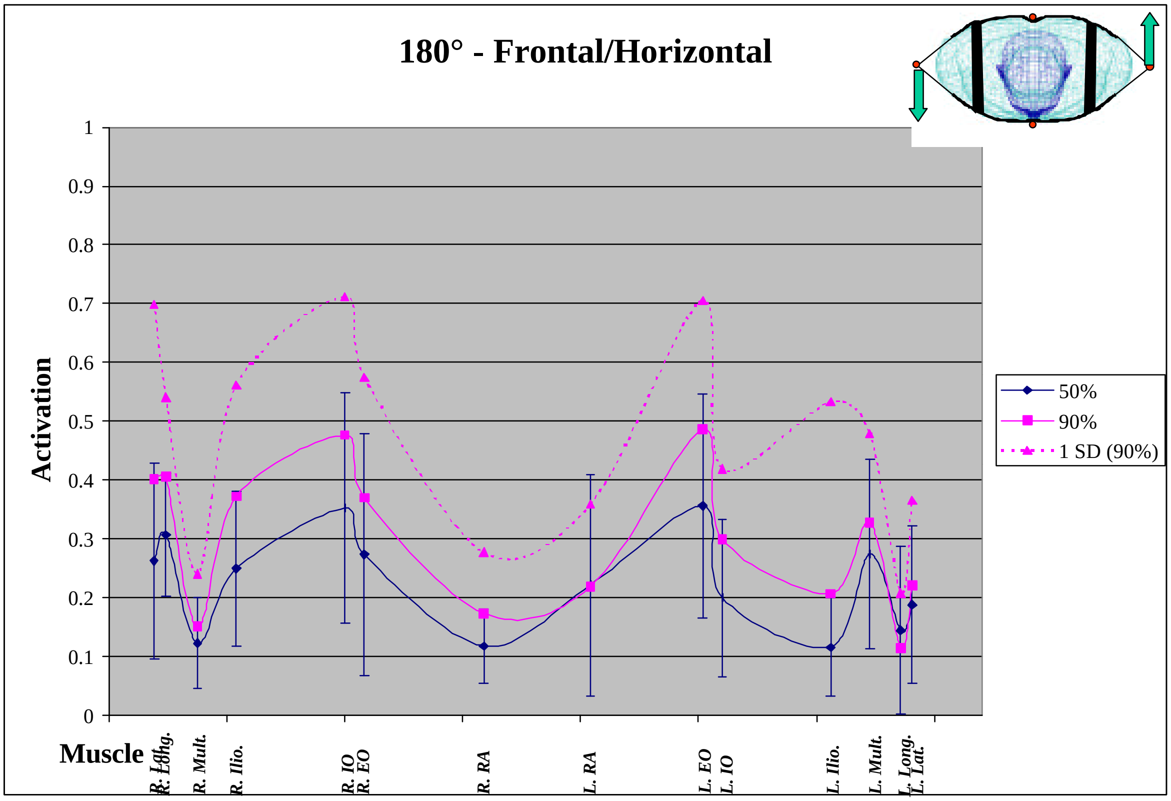

Figure 19. Muscle activation pattern for applied counterclockwise twisting

In the loading condition presented in Figure 11 (applied lateral bending), the muscle activation pattern appears to be low. To further examine whether different inter-subject patterns were responsible, graphs for this condition were generated per individual. The resulting graph is shown in Figure 20. The graph shows considerable differences between the pattern of activation followed by the participants, especially for subjects 2 and 7. The reason for this difference cannot be explained from any of the data gathered. However, the differences between this pair of participants and the others continued over most of the other loading conditions. Participant 1 also behaved out of the norm for some conditions, although the differences were only for a small set of muscles.

The inter-individual differences shown in Figure 20, however, do not explain the low overall activation levels observed in Figure 11. One plausible explanation is that participants did not perform to their maximum for these trials. The discussion section goes into further detail regarding this result.

The second dependent variable collected were the forces and moments measured on the force plate. These forces and moments were manipulated to obtain the corresponding values for the L3/L4 disc. An ANOVA was performed on the L3/L4 moments, and its results are shown in Table 8.

The ANOVA shows that the main effects of Magnitude (50% or 90%), Direction (combination of orientation and plane), Type (whether estimated from the EMG data or obtained through the force plate data), and Moment (sagittal, frontal or horizontal) are significant, while Repetition, and Gender are not. The Type factor was also significant in some of the two-way and higher interactions, however, indicating that variations in some of the other factors were better explained when the level of Type was considered. This result would have probably varied if the gain parameter had been modified individually for each subject to minimize the error between moment calculations, or if different gains were calculated for the flexor and extensor muscles (Nussbaum and Chaffin, 1998). However, such a minimization process would require extensively utilizing individual participant's data, which would limit the generalizability of the models analyzed here, since they would not be entirely predictive.

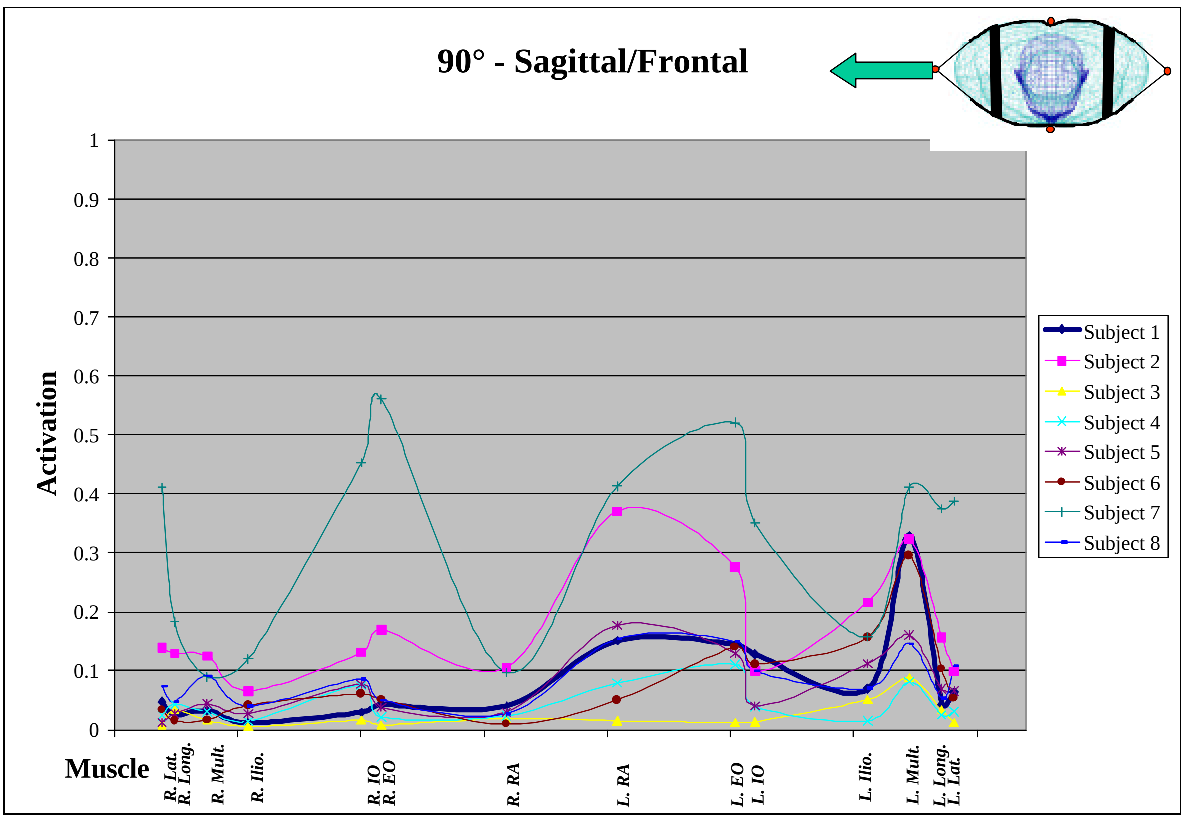

Figure 20. Inter-individual differences in applied lateral bending.

Table 8. ANOVA for L3/L4 Moments

Source	DF	SS	MS	F	P
Between Subject					
Gender	1	38	38	0.01	0.926
Subject(Gender)	6	19637	3273		
Within Subject					
Magnitude	1	4546	4546	13.37	0.01 *
Magnitude*Gender	1	538	538	1.58	0.26
Magnitude*Subject(Gender)	6	2040	340		
Direction	10	479336	47934	59.54	0.00 *
Direction*Gender	10	5779	578	0.72	0.70
Direction*Subject(Gender)	60	48304	805		
Repetition	1	0	0	0.00	1.00
Repetition*Gender	1	914	914	10.58	0.02 *
Repetition*Subject(Gender)	6	519	86		
Moment	2	117738	58869	12.78	0.00 *
Moment*Gender	2	3918	1959	0.43	0.66
Moment*Subject(Gender)	12	55288	4607		
Type	1	41604	41604	10.59	0.02 *
Type*Gender	1	4003	4003	1.02	0.35
Type*Subject(Gender)	6	23568	3928		
Magnitude*Direction	10	30726	3073	12.35	0.00 *
Magnitude*Direction*Gender	10	2196	220	0.88	0.55
Magnitude*Direction*Subject(Gender)	60	14931	249		
Magnitude*Repetition	1	1	1	0.02	0.88
Magnitude*Repetition*Gender	1	54	54	0.89	0.38
Magnitude*Repetition*Subject(Gender)	6	367	61		
Magnitude*Moment	2	3937	1968	8.53	0.01 *
Magnitude*Moment*Gender	2	164	82	0.35	0.71
Magnitude*Moment*Subject(Gender)	12	2769	231		
Magnitude*Type	1	219	219	2.61	0.16
Magnitude*Type*Gender	1	763	763	9.10	0.02 *
Magnitude*Type*Subject(Gender)	6	503	84		
Direction*Repetition	10	1287	129	0.67	0.75
Direction*Repetition*Gender	10	1966	197	1.02	0.44
Direction*Repetition*Subject(Gender)	60	11556	193		
Direction*Moment	20	1031615	51581	67.41	0.00 *
Direction*Moment*Gender	20	23569	1178	1.54	0.08
Direction*Moment*Subject(Gender)	120	91824	765		
Direction*Type	10	165752	16575	12.00	0.00 *
Direction*Type*Gender	10	7584	758	0.55	0.85
Direction*Type*Subject(Gender)	60	82902	1382		
Repetition*Moment	2	568	284	1.34	0.30
Repetition*Moment*Gender	2	226	113	0.53	0.60
Repetition*Moment*Subject(Gender)	12	2544	212		
Repetition*Type	1	44	44	0.20	0.67
Repetition*Type*Gender	1	374	374	1.74	0.24
Repetition*Type*Subject(Gender)	6	1290	215		
Moment*Type	2	116662	58331	28.25	0.00 *
Moment*Type*Gender	2	7955	3978	1.93	0.19
Moment*Type*Subject(Gender)	12	24777	2065		
Magnitude*Direction*Repetition	10	837	84	0.48	0.89
Magnitude*Direction*Repetition*Gender	10	1800	180	1.04	0.42
Magnitude*Direction*Repetition*Subject(Gender)	60	10362	173		
Magnitude*Direction*Moment	20	65292	3265	28.97	0.00 *
Magnitude*Direction*Moment*Gender	20	3692	185	1.64	0.05
Magnitude*Direction*Moment*Subject(Gender)	120	13523	113		

Table 8. ANOVA for L3/L4 Moments (cont.)

Magnitude*Direction*Type	10	6416	642	3.40	0.00 *
Magnitude*Direction*Type*Gender	10	1787	179	0.95	0.50
Magnitude*Direction*Type*Subject(Gender)	60	11316	189		
Magnitude*Repetition*Moment	2	60	30	0.64	0.55
Magnitude*Repetition*Moment*Gender	2	16	8	0.17	0.84
Magnitude*Repetition*Moment*Subject(Gender)	12	564	47		
Magnitude*Repetition*Type	1	0	0	0.00	1.00
Magnitude*Repetition*Type*Gender	1	112	112	2.21	0.19
Magnitude*Repetition*Type*Subject(Gender)	6	304	51		
Magnitude*Moment*Type	2	6025	3012	20.99	0.00 *
Magnitude*Moment*Type*Gender	2	274	137	0.96	0.41
Magnitude*Moment*Type*Subject(Gender)	12	1722	144		
Direction*Repetition*Moment	20	1925	96	0.80	0.71
Direction*Repetition*Moment*Gender	20	2848	142	1.18	0.28
Direction*Repetition*Moment*Subject(Gender)	120	14470	121		
Direction*Repetition*Type	10	966	97	0.49	0.89
Direction*Repetition*Type*Gender	10	1931	193	0.98	0.47
Direction*Repetition*Type*Subject(Gender)	60	11812	197		
Direction*Moment*Type	20	249569	12478	13.62	0.00 *
Direction*Moment*Type*Gender	20	14608	730	0.80	0.71
Direction*Moment*Type*Subject(Gender)	120	109951	916		
Repetition*Moment*Type	2	403	202	3.65	0.06
Repetition*Moment*Type*Gender	2	591	296	5.36	0.02 *
Repetition*Moment*Type*Subject(Gender)	12	662	55		
Magnitude*Direction*Repetition*Moment	20	1768	88	0.93	0.55
Magnitude*Direction*Repetition*Moment*Gender	20	1508	75	0.79	0.72
Magnitude*Direction*Repetition*Moment*Subject(Gender)	120	11425	95		
Magnitude*Direction*Repetition*Type	10	1150	115	0.73	0.69
Magnitude*Direction*Repetition*Type*Gender	10	3212	161	1.29	0.20
Magnitude*Direction*Repetition*Type*Subject(Gender)	60	9459	158		
Magnitude*Direction*Moment*Type	20	10273	514	4.12	0.00 *
Magnitude*Direction*Moment*Type*Gender	20	3024	151	1.21	0.26
Magnitude*Direction*Moment*Type*Subject(Gender)	120	14957	125		
Magnitude*Repetition*Moment*Type	2	270	135	3.82	0.05
Magnitude*Repetition*Moment*Type*Gender	2	124	62	1.76	0.21
Magnitude*Repetition*Moment*Type*Subject(Gender)	12	424	35		
Direction*Repetition*Moment*Type	20	1967	98	1.20	0.26
Direction*Repetition*Moment*Type*Gender	20	2221	111	1.36	0.16
Direction*Repetition*Moment*Type*Subject(Gender)	120	9800	82		
Magnitude*Direction*Repetition*Moment*Type	20	1228	61	0.83	0.67
Magnitude*Direction*Repetition*Moment*Type*Gender	20	1025	51	0.69	0.83
Magnitude*Direction*Repetition*Moment*Type*Subject(Gender)	120	8876	74		
Total	2111	3056305			

(*) denotes significance at a = 0.05

A third dependent variable was analyzed as well. Since participants had to develop MVE's on two different sessions, it was possible that different MVE levels were developed on each day. If this were the case, the loads applied on the second day (which where determined from the MVE's obtained on the first day) might differ significantly from the desired levels (i.e.

50% and 90% of MVE). Table 9 shows the results of the ANOVA on MVE's. The only significant main effect or interaction was Direction, which includes flexion, extension, lateral bending and twist, and was expected to be significant.

Table 9. ANOVA for MVE's

Source	DF	SS	MS	F	P	
Between Subject						
Gender	1	128	128	0.11	0.75	
Subject(Gender)	6	6780	1130			
Within Subject						
Direction	3	1762090	587363	69.93	0.00	*
Direction*Gender	3	31845	10615	1.26	0.32	
Direction*Subject(Gender)	18	151187	8399			
Repetition	1	60	60	0.12	0.74	
Repetition*Gender	1	601	601	1.22	0.31	
Repetition*Subject(Gender)	6	2966	494			
Day	1	216	216	0.56	0.48	
Day*Gender	1	343	343	0.88	0.38	
Day*Subject(Gender)	6	2328	388			
Direction*Repetition	3	1798	599	1.27	0.31	
Direction*Repetition*Gender	3	448	149	0.32	0.81	
Direction*Repetition*Subject(Gender)	18	8477	471			
Direction*Day	3	11275	3758	0.91	0.46	
Direction*Day*Gender	3	5962	1987	0.48	0.70	
Direction*Day*Subject(Gender)	18	74443	4136			
Repetition*Day	1	143	143	1.83	0.23	
Repetition*Day*Gender	1	99	99	1.27	0.30	
Repetition*Day*Subject(Gender)	6	469	78			
Direction*Repetition*Day	3	544	181	0.92	0.45	
Direction*Repetition*Day*Gender	3	433	144	0.73	0.55	
Direction*Repetition*Day*Subject(Gender)	18	3538	197			
Total	127	2066172				

(*) denotes significance at a = 0.05

4.2 Phase II: Model Data Collection

The data gathered in Phase I were used as inputs to the each of the models, which returned a predicted muscle activation pattern. Each model's output will be analyzed here against the EMG data collected, alternating between both quantitative and qualitative methods, as described in more detail in Nussbaum (1994) and Nussbaum and Chaffin (1996b).

When correctly evaluating the performance of predictive models of any kind, it is necessary to do so under a wide array of conditions. However, this poses a paradox in that the more data available, the harder it becomes to differentiate between models of similar performance, a problem first noted for some of the models in question by Hatze (1980). The difficulty arises in that the processing of large amounts of data tends to decrease the sensitivity of any test used, and this has indeed been the case for the models tested here. According to Hughes (1991), excessive data collection can be avoided to a certain extent by determining specific data points in which the model predictions differ from each other, prior to data collection. Detailed testing is then performed on those points to determine which model, if any, provides a better approximation.

However, for this particular work, the development of a comprehensive database was also a goal. Therefore, data was collected for a wide number of loading conditions, and is used here as a starting point for the model's comparison.

Tables 10 and 11 show the coefficients of determination and correlation between the models and the EMG data grouped by muscle and loading condition, respectively. Figures 21-31 show the average predicted patterns against the 50% average pattern for all loading conditions.

Table 10. Coefficients of determination and (Correlation) of each model against the EMG data, grouped by muscle. Averages are calculated for the coefficients of determination.

	Right Longissimus		Left Longissimus		Right Multifidus		Left Multifidus		Right Iliocostalis		Left Iliocostalis		Right Rectus Abdominis		Left Rectus Abdominis	
DMH Actual	0.00	(0.06)	0.52	(0.72)	0.63	(0.79)	0.64	(0.80)	0.20	(0.45)	0.36	(0.60)	0.69	(0.83)	0.27	(0.52)
SCI Actual	0.37	(0.61)	0.35	(0.59)	0.88	(0.94)	0.58	(0.76)	0.08	(0.28)	0.47	(0.69)	0.65	(0.80)	0.24	(0.49)
ANN Actual	0.64	(0.80)	0.32	(0.57)	0.88	(0.94)	0.25	(0.50)	0.31	(0.56)	0.57	(0.76)	0.53	(0.73)	0.21	(0.46)
Average	0.34		0.40		0.80		0.49		0.20		0.47		0.62		0.24	

	Right Latissimus		Left Latissimus		Right Internal Oblique		Left Internal Oblique		Right External Oblique		Left External Oblique		Average
DMH Actual	0.03	(0.18)	0.31	(0.56)	0.46	(0.68)	0.79	(0.89)	0.62	(0.78)	0.03	(0.16)	0.40
SCI Actual	0.04	(0.19)	0.20	(0.45)	0.33	(0.57)	0.61	(0.78)	0.45	(0.67)	0.29	(0.54)	0.40
ANN Actual	0.01	(0.08)	0.25	(0.50)	0.25	(0.50)	0.28	(0.53)	0.36	(0.60)	0.20	(0.44)	0.36
Average	0.03		0.25		0.35		0.56		0.48		0.17		

Table 11. Coefficients of determination and (Correlation) of each model against the EMG data, grouped by loading condition. Averages are calculated for the coefficients of determination.

	0° - Sagittal Frontal		45° - Sagittal Frontal		90° - Sagittal Frontal		135° - Sagittal Frontal		180° - Sagittal Frontal		45° - Sagittal Horizontal	
DMH Actual	0.33	(0.57)	0.52	(0.72)	0.41	(0.64)	0.30	(0.55)	0.59	(0.76)	0.32	(0.57)
SCI Actual	0.57	(0.75)	0.44	(0.66)	0.31	(0.55)	0.40	(0.63)	0.56	(0.75)	0.54	(0.73)
ANN Actual	0.07	(0.26)	0.04	(0.19)	0.22	(0.47)	0.38	(0.62)	0.23	(0.48)	0.19	(0.44)
Average	0.32		0.33		0.31		0.36		0.46		0.35	

	90° - Sagittal Horizontal		135° - Sagittal Horizontal		45° - Frontal Horizontal		135° - Frontal Horizontal		180° - Frontal Horizontal		Average
DMH Actual	0.46	(0.67)	0.18	(0.43)	0.58	(0.76)	0.15	(0.39)	0.18	(0.43)	0.37
SCI Actual	0.48	(0.69)	0.31	(0.55)	0.47	(0.68)	0.41	(0.64)	0.47	(0.69)	0.45
ANN Actual	0.35	(0.59)	0.21	(0.45)	0.23	(0.48)	0.31	(0.56)	0.35	(0.59)	0.23
Average	0.43		0.23		0.43		0.29		0.33		

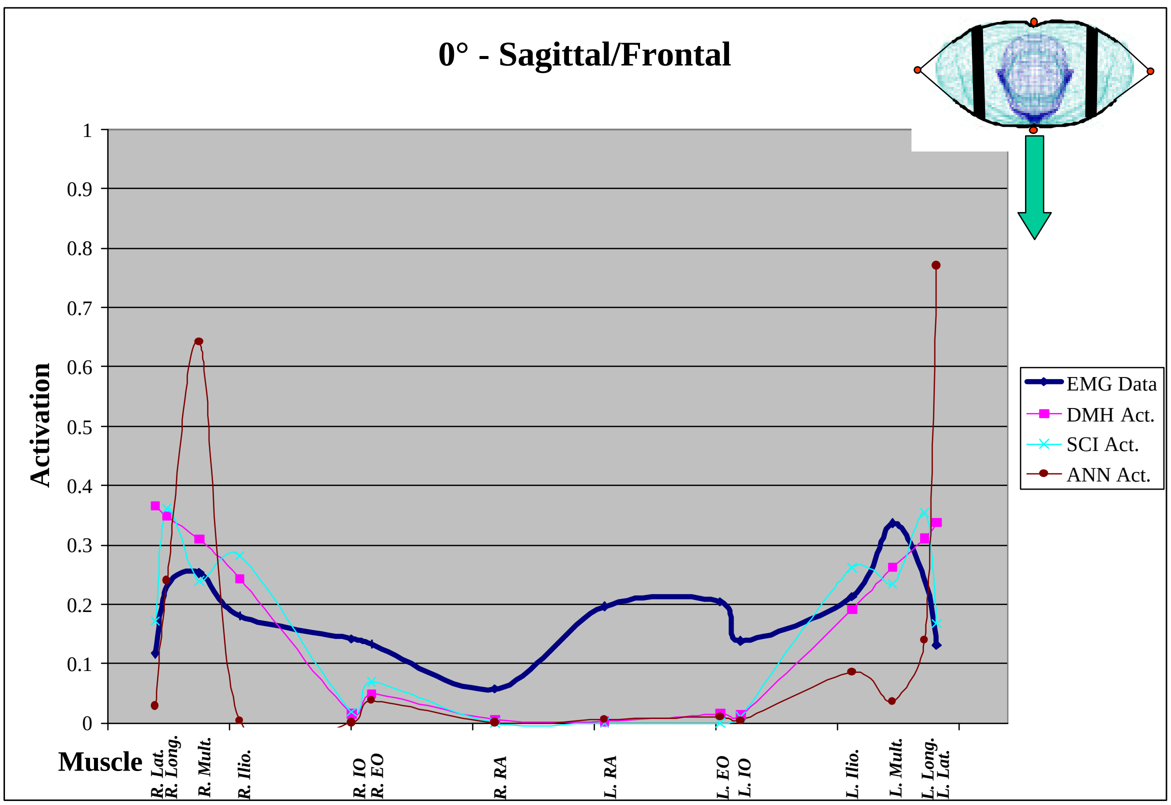

Figure 21. Model predictions against EMG Data

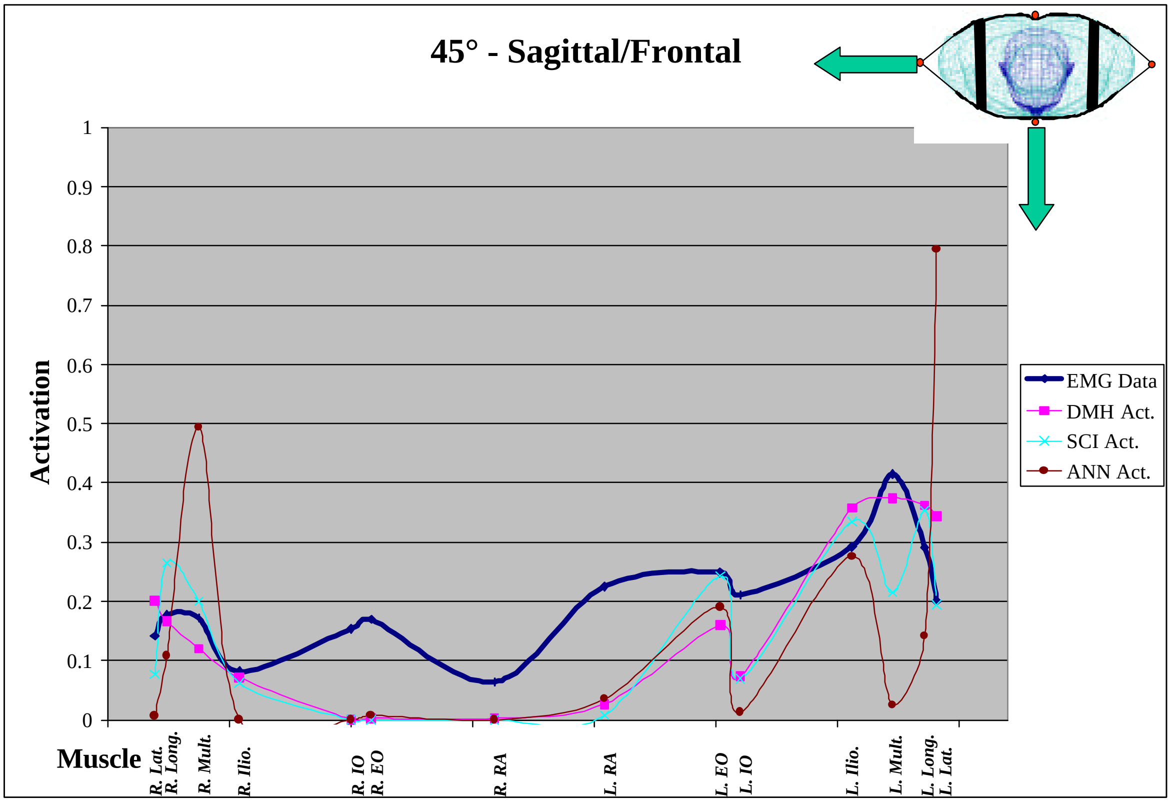

Figure 22. Model predictions against EMG Data

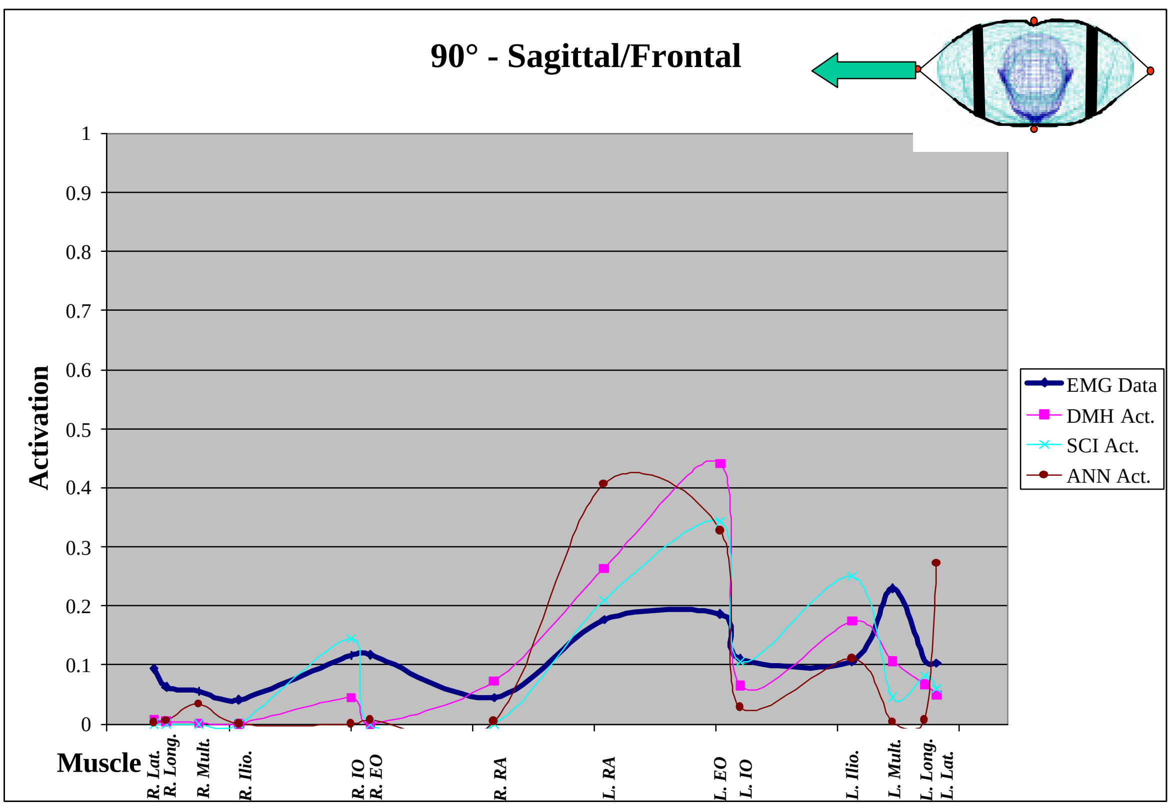

Figure 23. Model predictions against EMG Data

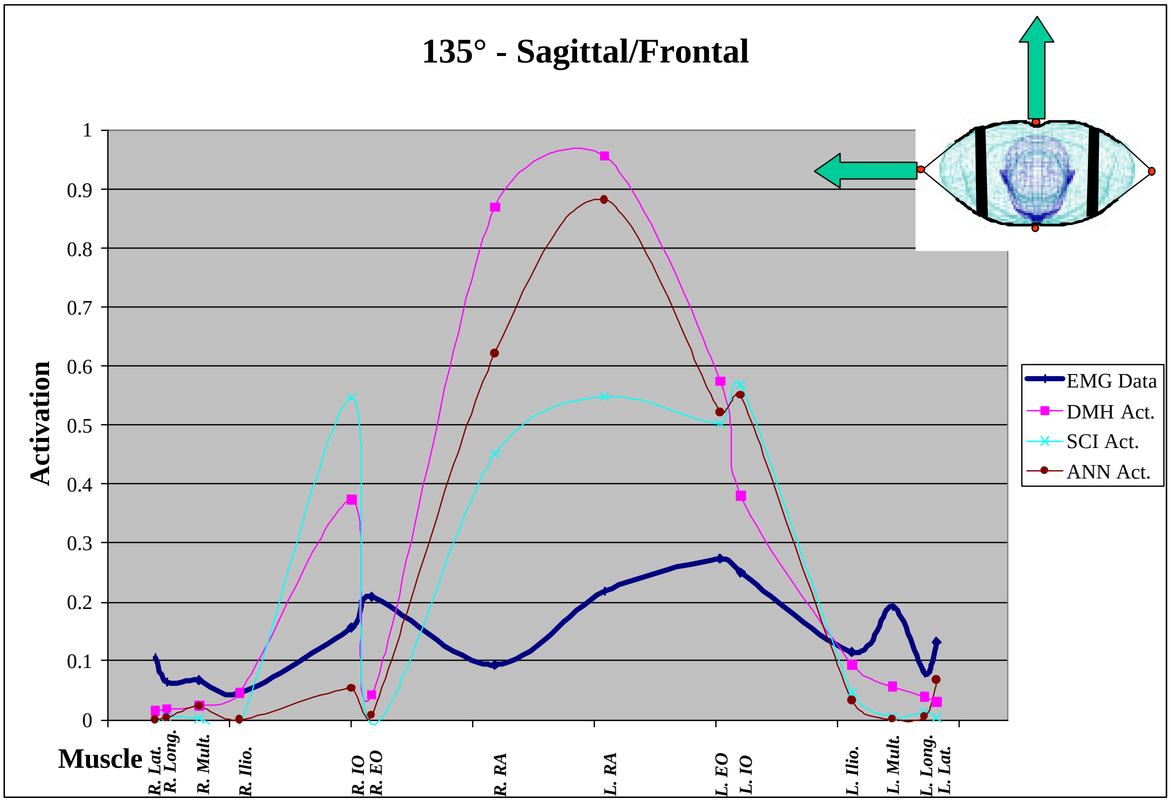

Figure 24. Model predictions against EMG Data

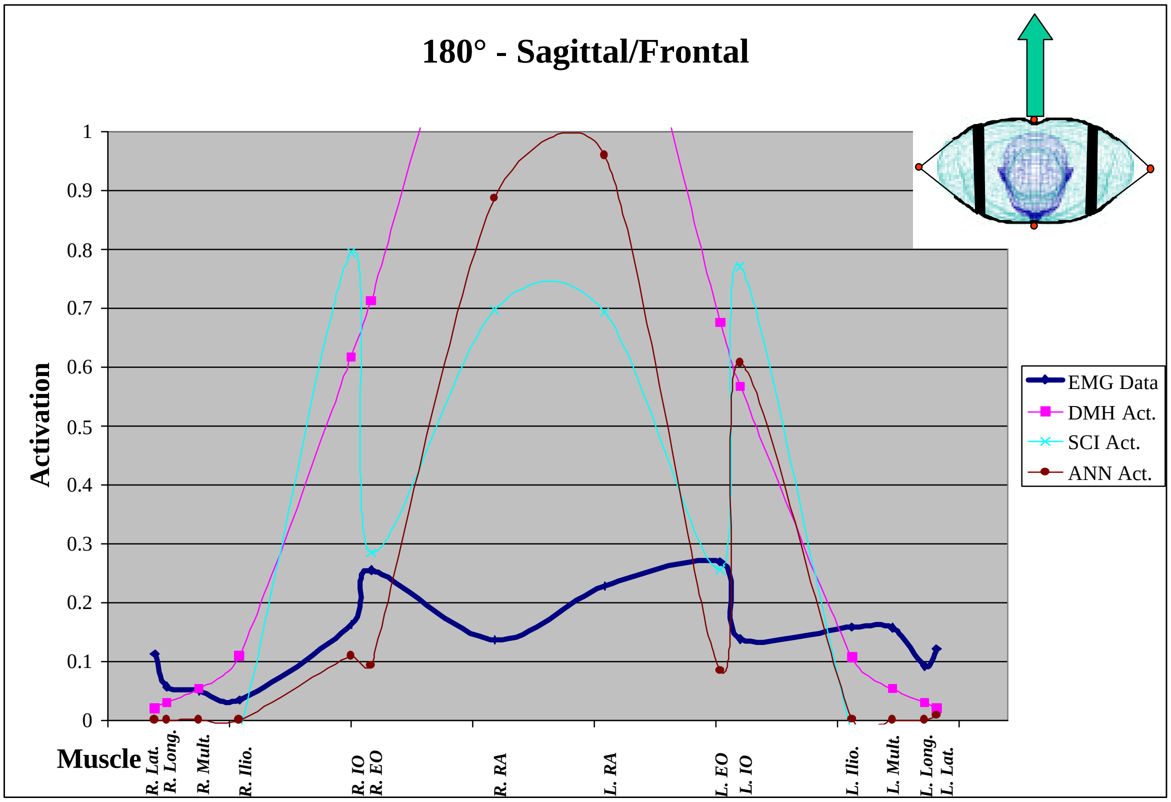

Figure 25. Model predictions against EMG Data

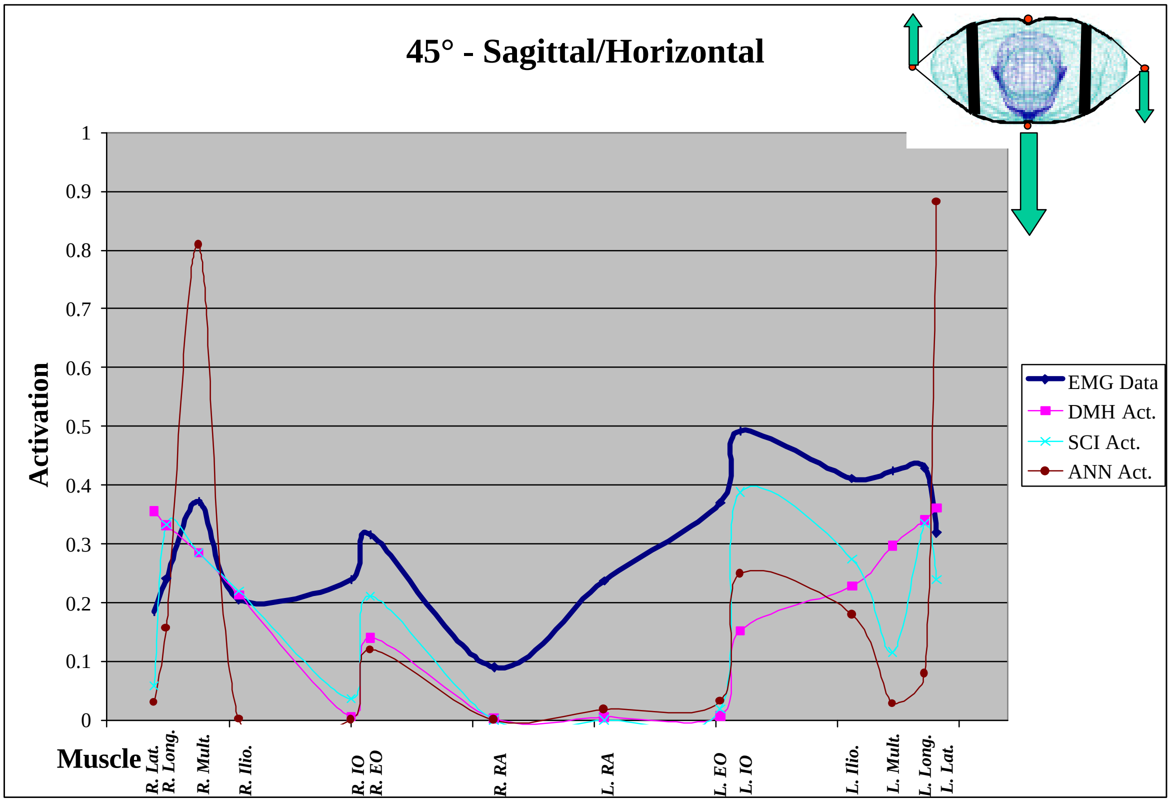

Figure 26. Model predictions against EMG Data

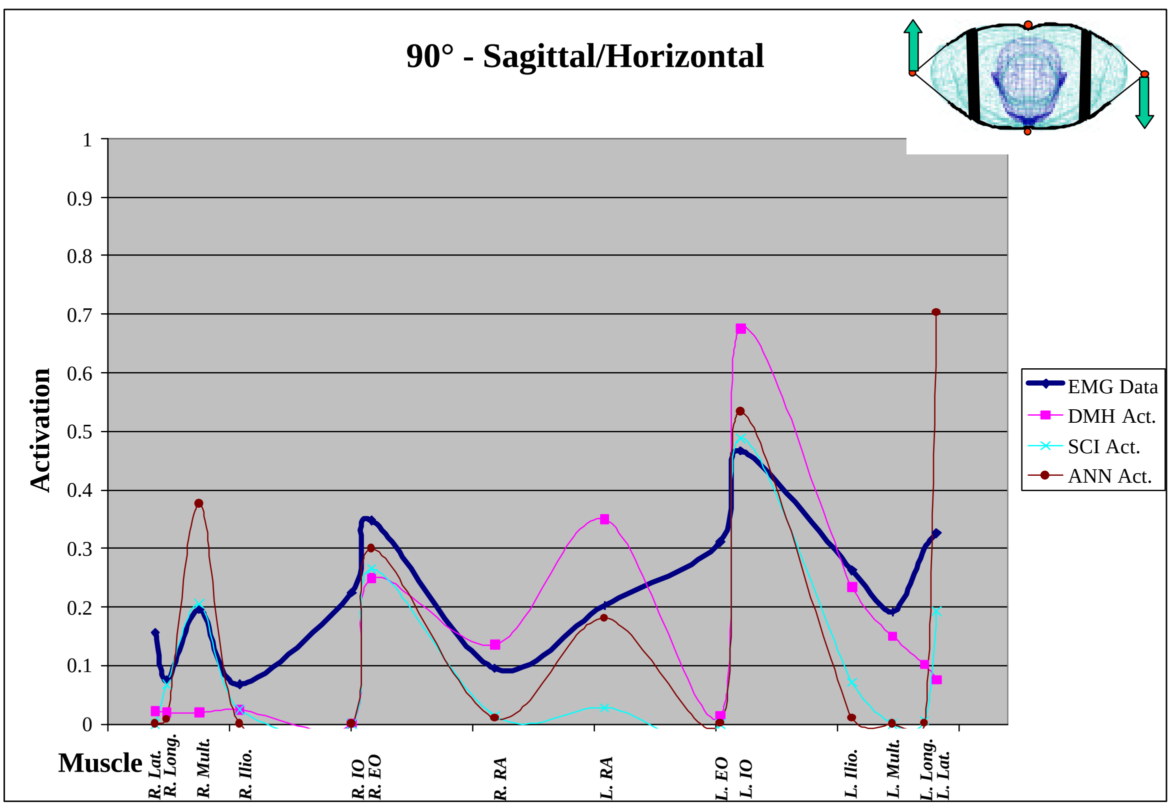

Figure 27. Model predictions against EMG Data

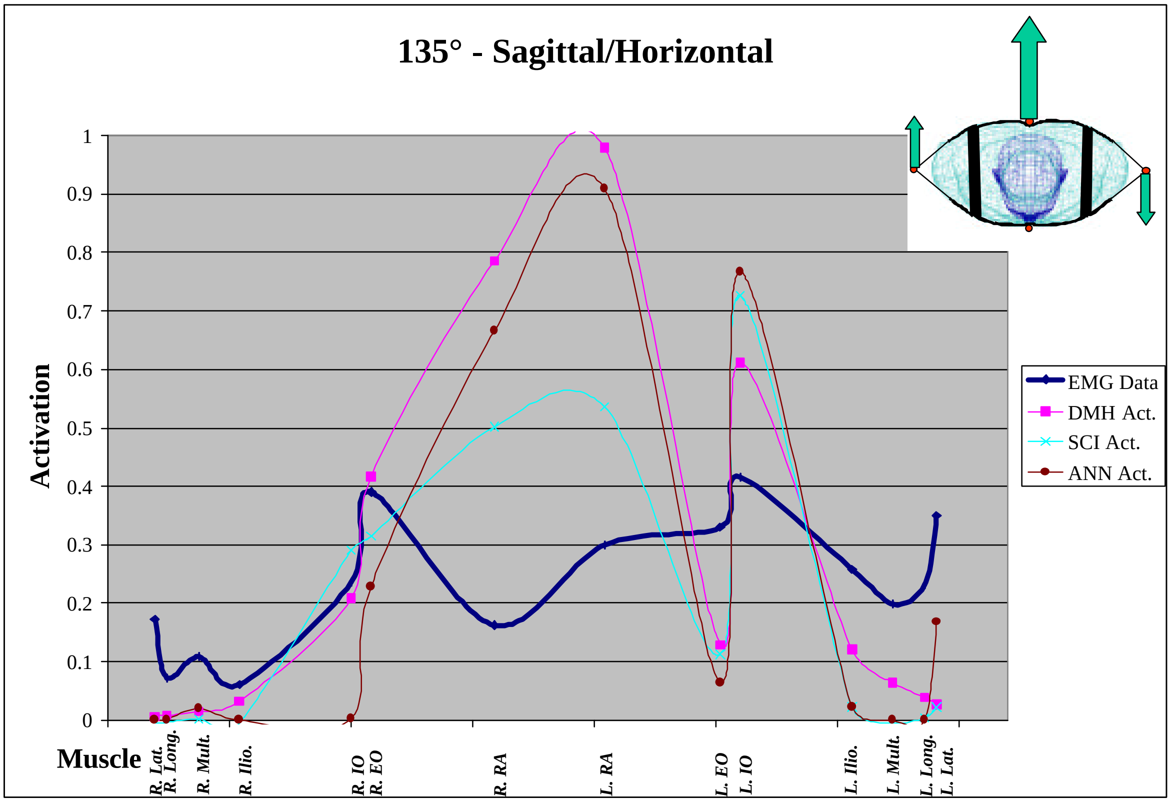

Figure 28. Model predictions against EMG Data

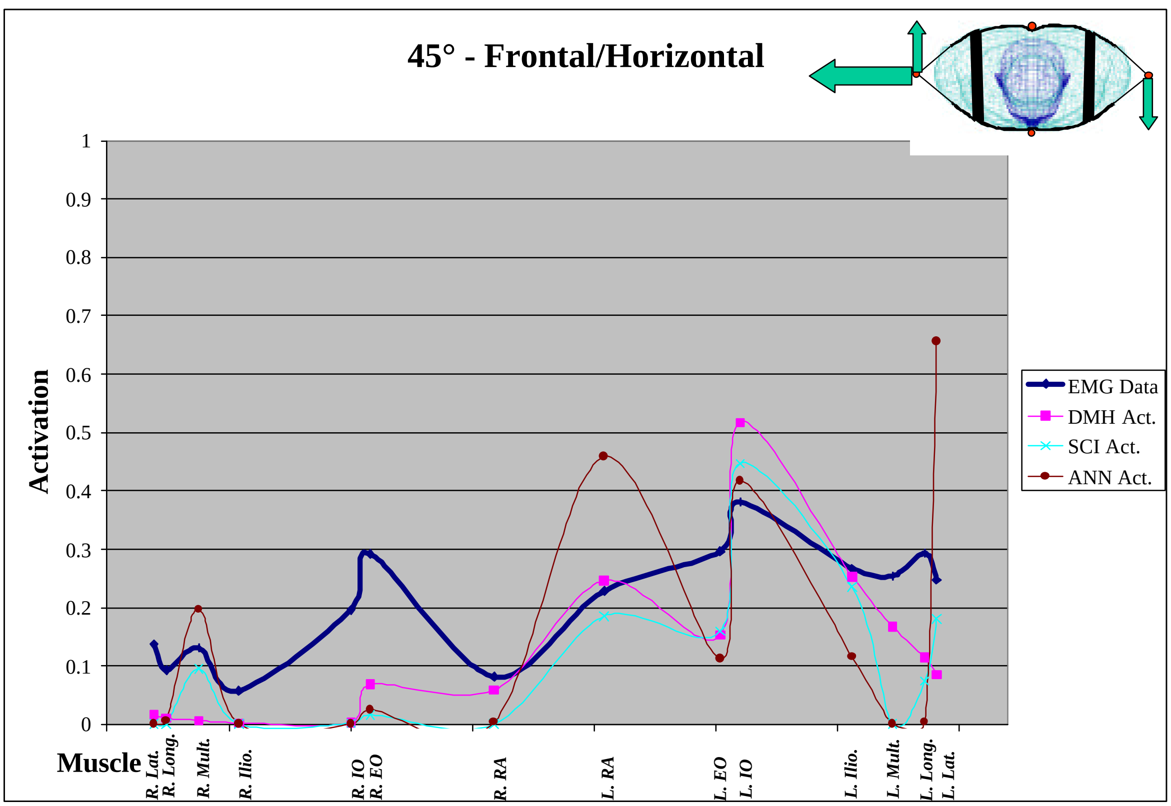

Figure 29. Model predictions against EMG Data

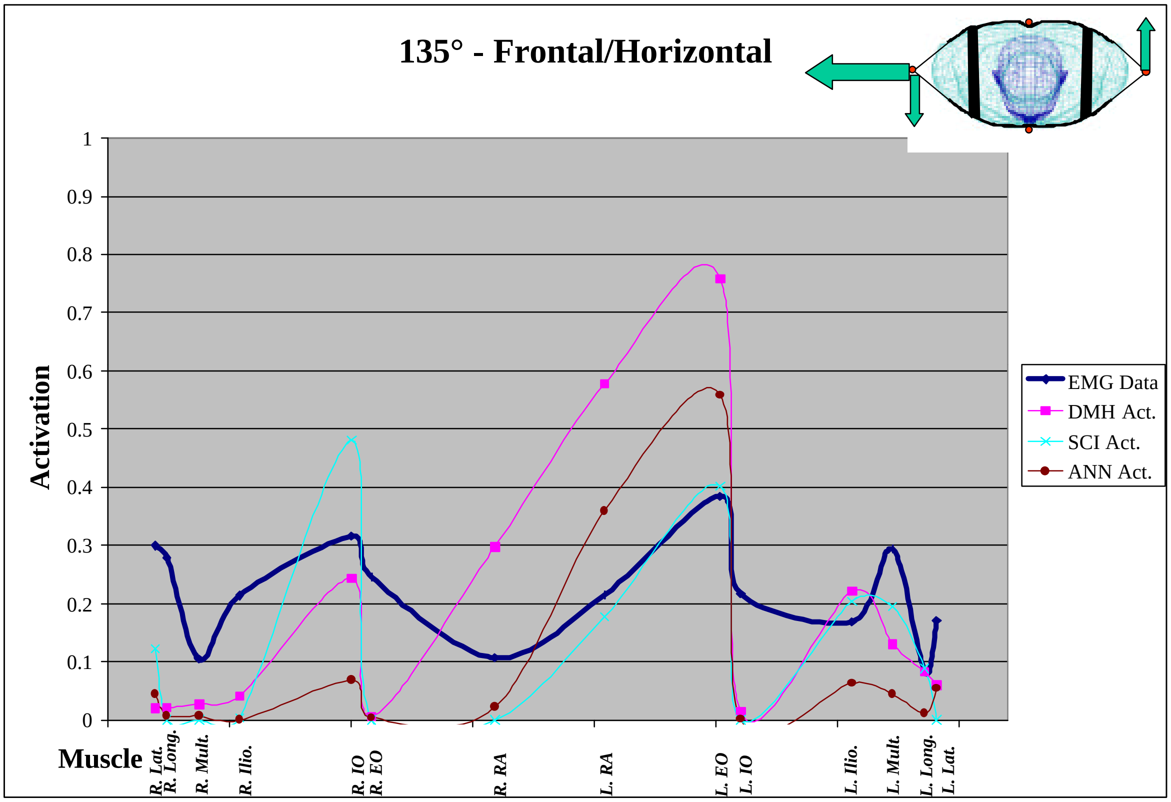

Figure 30. Model predictions against EMG Data

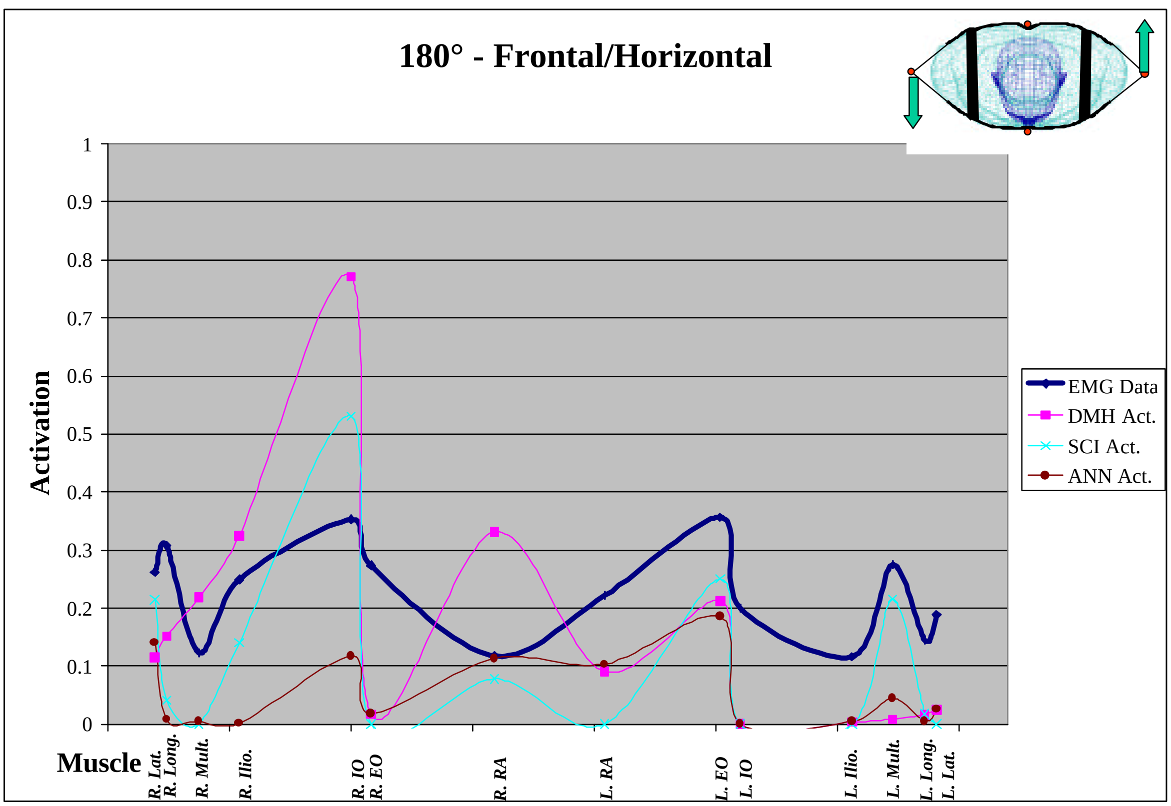

Figure 31. Model predictions against EMG Data

Some researchers have tried to define muscle activation patterns in terms of the activation state of the muscle (i.e. active or silent), and the specific loading patterns from which a muscle goes from the silent state to the active state or vice-versa (see Ladin, et al., 1989). One drawback of this technique is that an activation level, usually arbitrarily picked, must be defined as the threshold. Nevertheless, an accurate model should be able to predict active-silent states.

The qualitative technique used to summarize the activation state information uses truth tables, which consist of four cells of data that show the agreement between the measured muscle state and the predicted muscle state. Table 12 shows the results of this analysis for the models under study. For the truth tables shown, the threshold level selected was 5%, therefore, a muscle activation higher that 5% indicates an active muscle.

Table 12. Truth tables for the models under consideration. Each entry indicates the percentage of occurrences in each category as a function of the total number of entries in the column. The threshold selected was 5%

DMH

		Measured	
		Active	***Silent***
Predicted	***Active***	64.82%	41.05%
	Silent	35.18%	58.95%

SCI

		Measured	
		Active	***Silent***
Predicted	***Active***	54.60%	23.39%
	Silent	45.40%	76.61%

ANN

		Measured	
		Active	***Silent***
Predicted	***Active***	41.37%	12.16%
	Silent	58.63%	87.84%

The final testing category used here consists of model adherence to constraints imposed by their inputs. All models were input moments, and their resultant activation levels, when properly transformed, should equilibrate those moments as closely as possible. Tables 13 and 14 show the average coefficients of determination, correlation coefficients, and equilibration errors per model. A particular variable of interest when using these models are compression predictions for the joint under study. Average compression predictions for each loading condition, grouped by model, are presented in Table 15. The next chapter discusses the results presented in this chapter in further detail.

Table 13. Average equilibration errors per model and moment plane (Nm)

Plane		Model: DMH	SCI	ANN
	Sagittal	10.28	0.00	21.13
	Frontal	15.47	0.00	11.88
	Horizontal	8.39	0.00	17.67

Table 14. Coefficients of determination and correlation for moment equilibration, organized per model

	Model: DMH	SCI	ANN
R-square	0.94	1.00	0.87
Correlation	0.97	1.00	0.93

Table 15. Compression force predictions. The p-values indicate significant difference against EMG estimate.

Loading Condition (50% Magnitude)

	1	2	3	4	5	6	7	8	9	10	11	p-value
EMG	1132.4	1209.8	610.7	752.7	750.4	1840.8	1277.5	1251.1	1195.1	1244.0	1303.1	
DMH	1129.0	1031.6	511.4	1116.0	1856.4	1223.2	765.0	1088.3	654.8	923.1	868.2	0.95
SCI	1116.0	1012.8	507.2	845.5	997.5	1206.4	501.3	769.4	524.5	645.7	540.1	0.023
ANN	775.7	805.8	401.7	839.5	766.0	933.2	650.0	818.9	596.1	444.3	244.3	0.0004

Loading Condition (90% Magnitude)

	1	2	3	4	5	6	7	8	9	10	11	p-value
EMG	1902.8	1508.6	707.3	707.9	908.7	2493.0	1855.8	1814.7	1665.5	1577.0	1721.8	
DMH	1917.1	1669.8	939.8	1962.8	2987.1	2045.7	1176.5	1899.4	976.5	1657.2	1252.2	0.95
SCI	1860.6	1605.7	889.0	1188.4	1503.1	1896.0	862.5	1143.0	747.9	1154.4	837.6	0.023
ANN	1307.4	1348.6	761.4	1178.0	1035.6	1497.4	955.9	1091.0	922.5	927.5	560.4	0.0004

Chapter 5. DISCUSSION

5.1 EMG Data Collection

In general, the cross-section of loading conditions in this study that were compatible with the Lavender, et al. (1992a, 1992b) studies showed similar muscle activation patterns. This agreement is important because to a limited extent it supports the rest of the data collected here, for which there is no published comparison. The main difference between the current study and the Lavender, et al. studies is the magnitude of the activation. However, this is expected, since the magnitude of the moments applied here is higher than the one used by Lavender, et al. While the average L3/L4 flexion moment applied in the *low* magnitude condition in the current study was 74.98 Nm, the largest moment applied by Lavender, et al. was 50 Nm. Thus, the current database builds onto the Lavender, et al. database for combined loading in the sagittal and frontal planes. Figures 32-39 illustrate the current database's predictions against the Lavender, et al. (1992a, 1992b) studies. Since the Lavender studies did not divide the erector spinae muscles into its component parts, comparison of this set of muscles is drawn against the longissimus muscle in the current study, based on similar electrode placements. No comparisons could be drawn for the internal oblique, multifidus, and iliocostalis muscle pairs because the placement of the electrodes in Lavender's studies was not compatible with detection of EMG signals from these muscles.

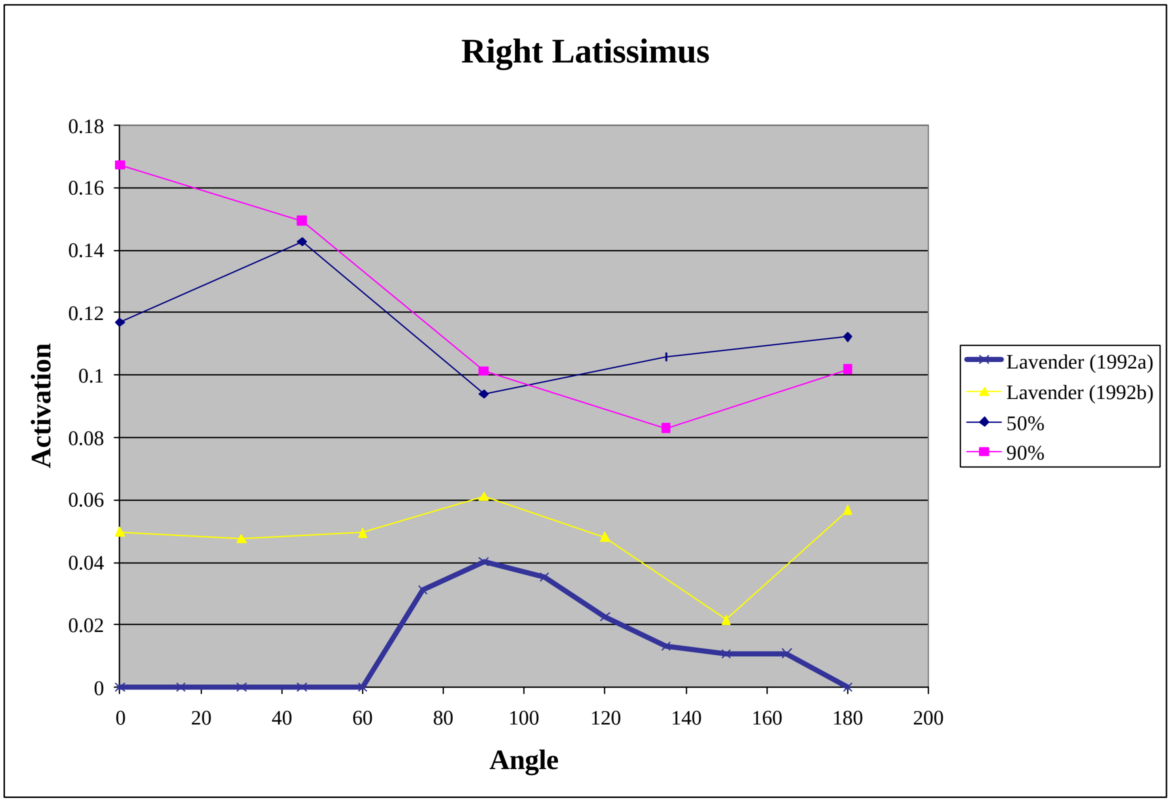

Figure 32. Lavender's data vs. the current database. Right Latissimus muscle.

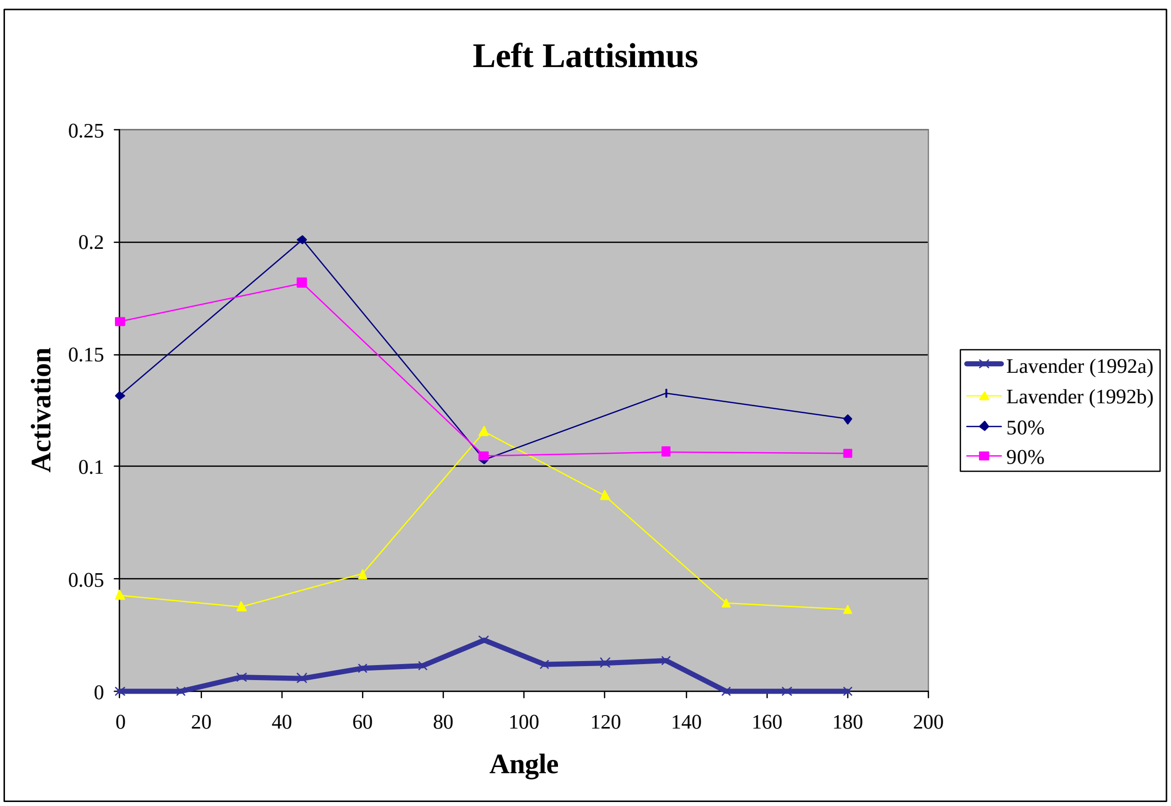

Figure 33. Lavender's data vs. the current database. Left Latissimus muscle.

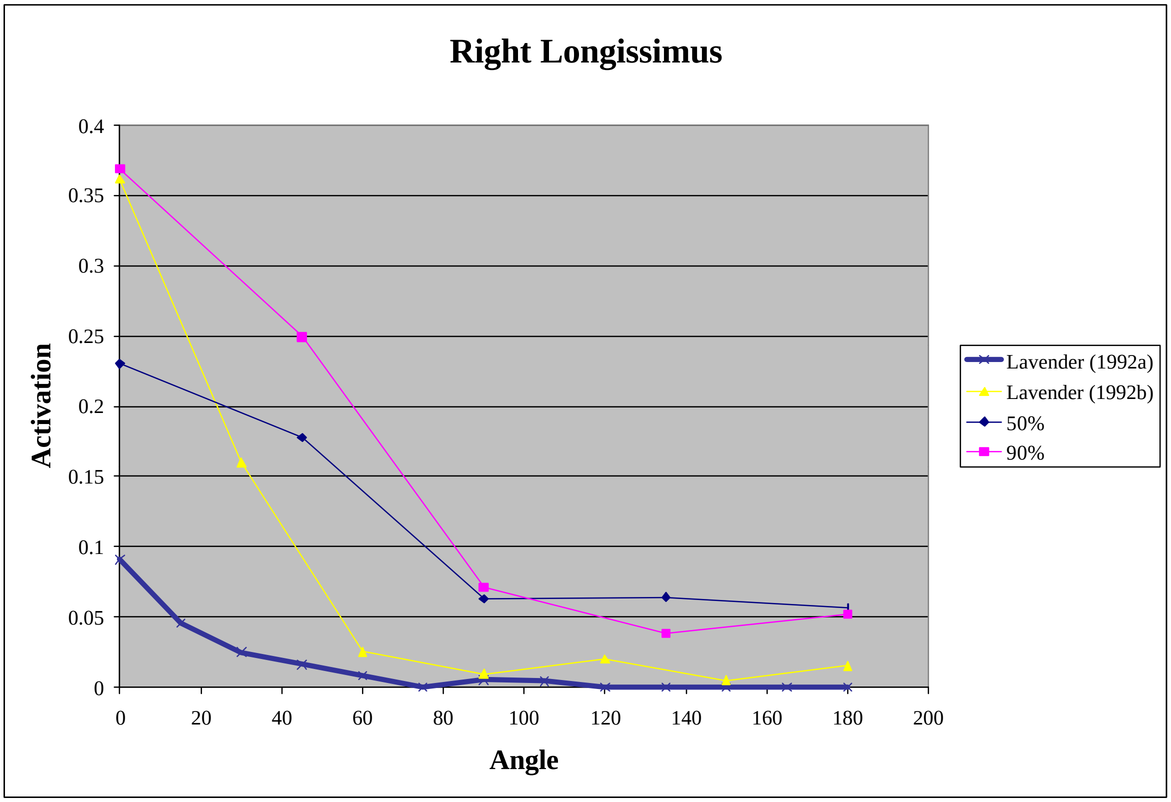

Figure 34. Lavender's data vs. the current database. Right Longissimus muscle.

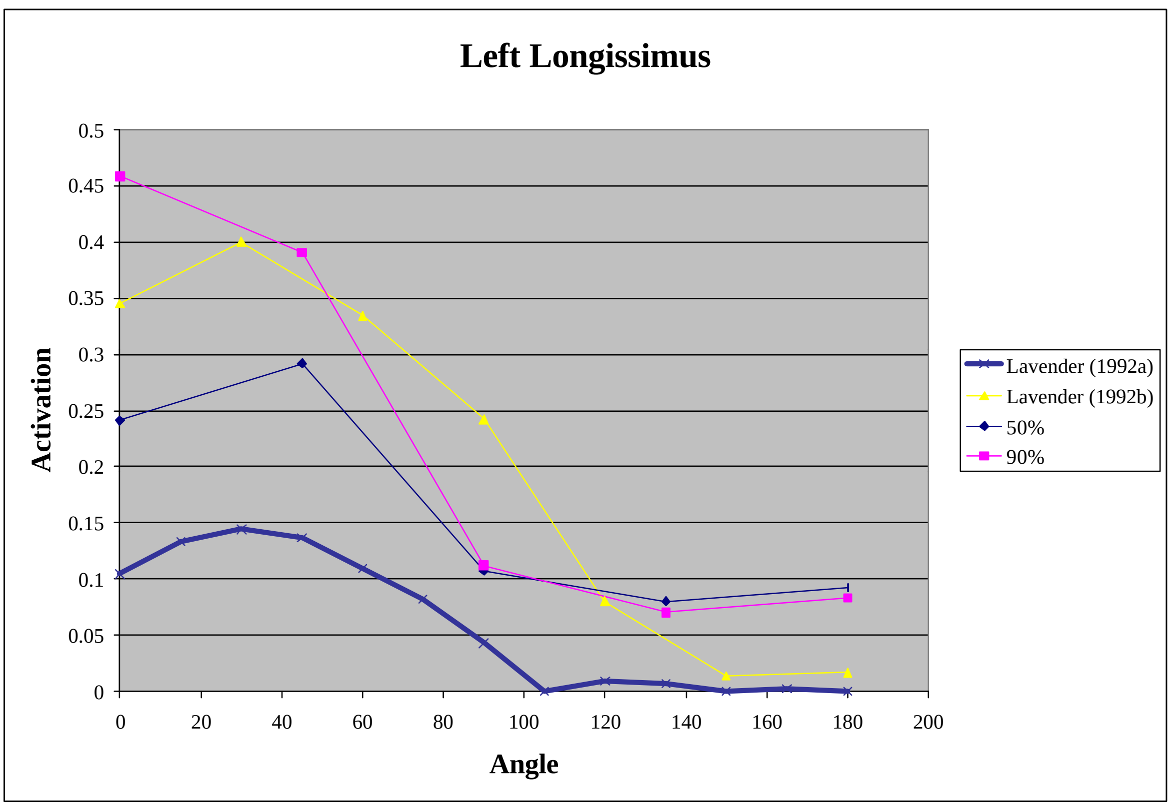

Figure 35. Lavender's data vs. the current database. Left Longissimus muscle.

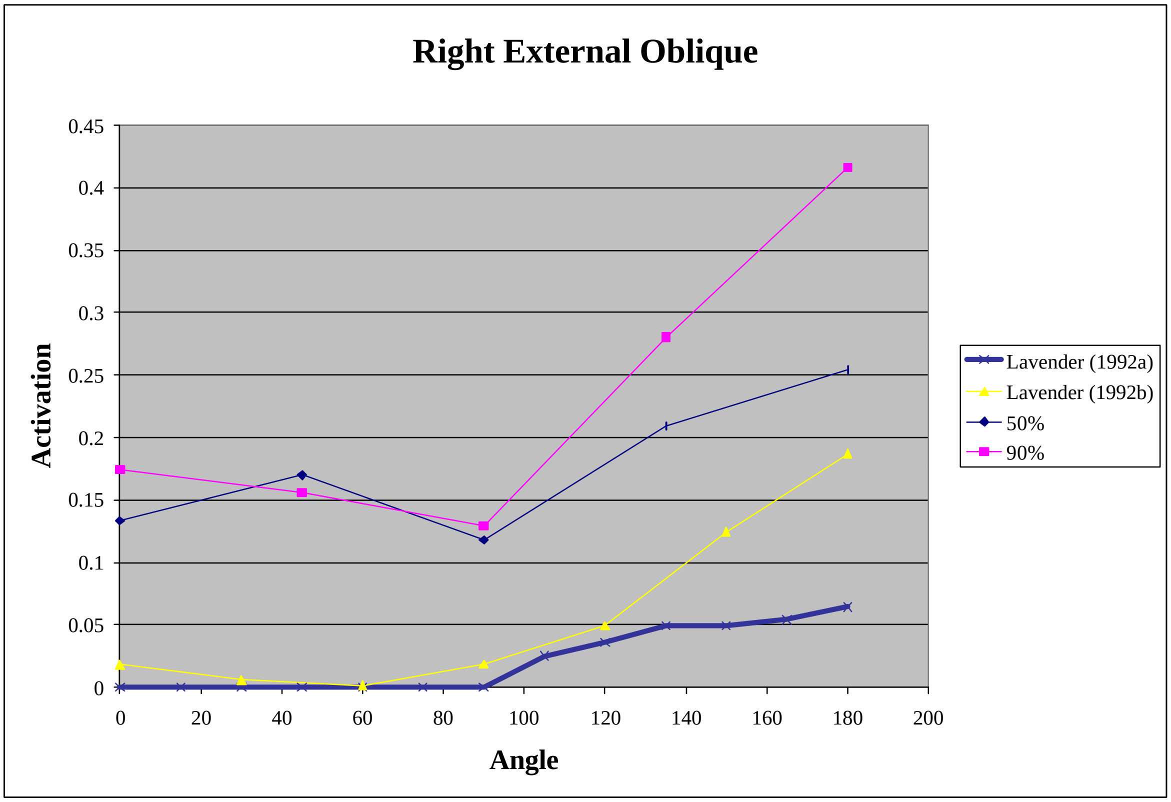

Figure 36. Lavender's data vs. the current database. Right External Oblique muscle.

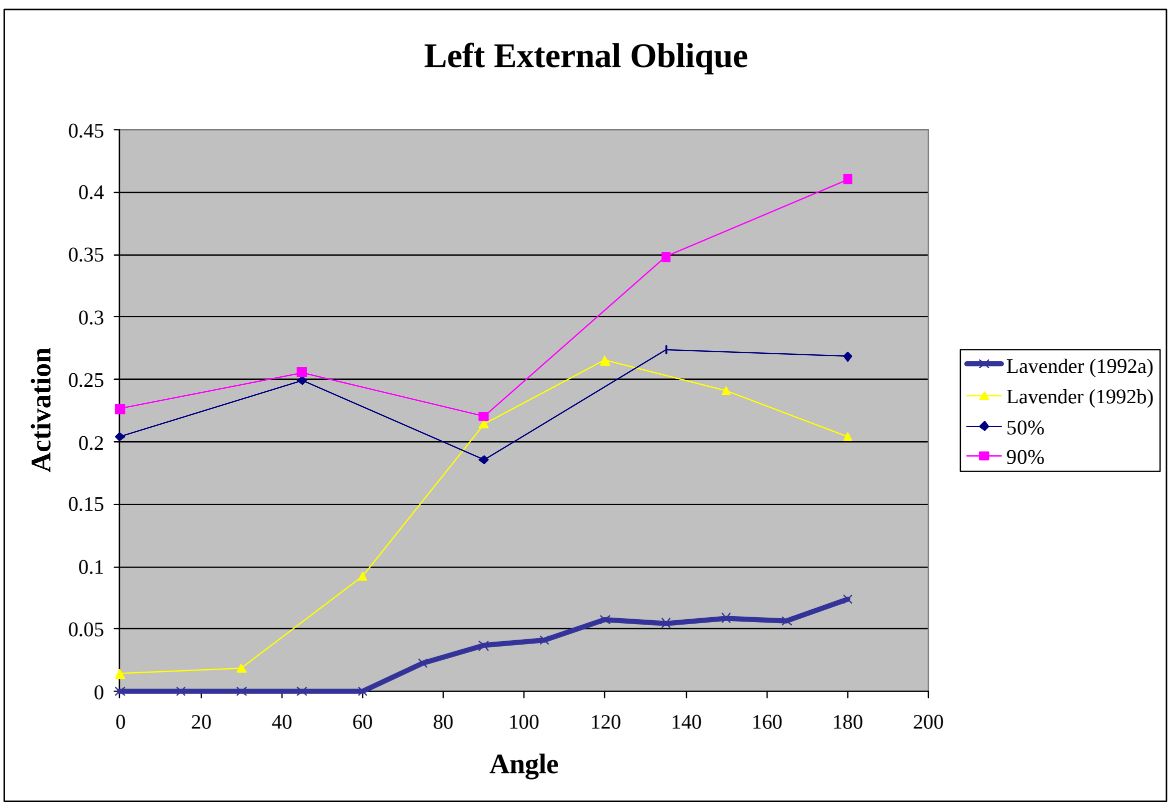

Figure 37. Lavender's data vs. the current database. Left External Oblique muscle.

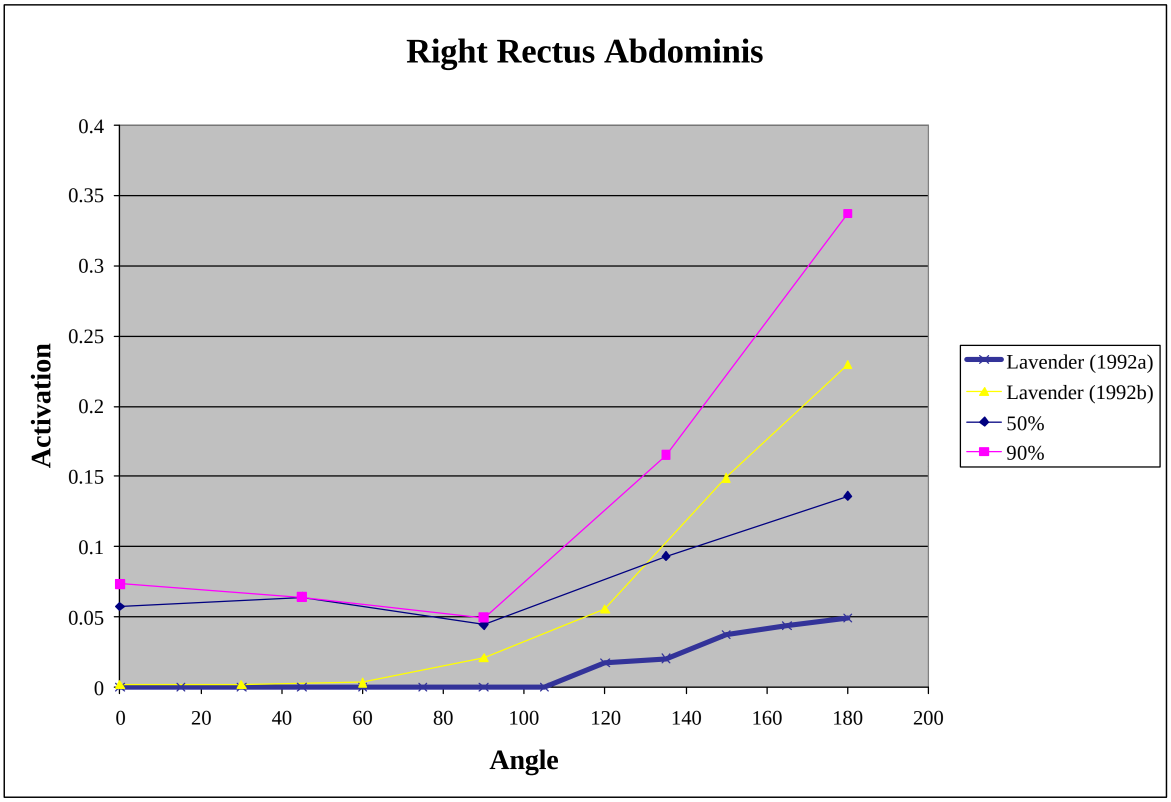

Figure 38. Lavender's data vs. the current database. Right Rectus Abdominis muscle.

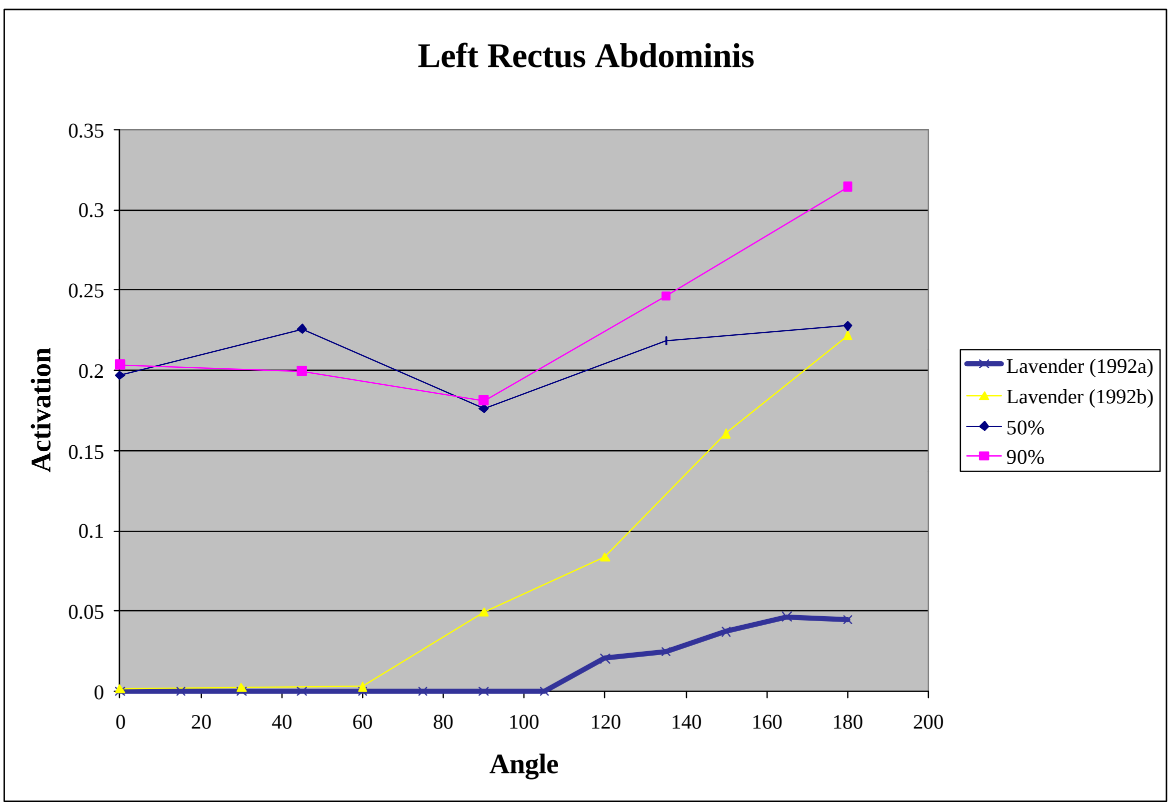

Figure 39. Lavender's data vs. the current database. Left Rectus Abdominis muscle.

Several specific results from the ANOVA performed on the activation patterns are of particular interest. Two factors that were non-significant offer the biggest insight here: Repetition and Gender. The non-significance of Repetition suggests that intra-subject differences (i.e. differences between repetitions of the same exertion) may not have to be considered when appropriate resting time is allowed between exertions of the type studied here. However, further study under other conditions (e.g. dynamic, bent-posture) is needed before it can be disregarded as an important modeling parameter.

The non-significance of Gender is important when viewed in combination with other results. Gender was not significant in any of the ANOVA's completed for this study, including EMG activation patterns, calculated L3/L4 moment, and calculated MVE moment (at L3/L4). Thus, matching female height and weight to the male height and weight seems to have minimized the differences between these two groups to the extent that there were no differences among them in terms of the dependent variables analyzed here. To a limited extent, this result also supports our assumptions that normalizing applied loads to the participant's MVE would serve as well to normalize the muscle activation patterns and that females would behave similar to males when appropriate allowance is made for anatomical differences. Any differences reported in other studies may be due to differences in muscle geometry.

However, the real effect of our normalization process is observed better in the variances plotted in Figures 9 to 19. Although some large standard deviations occur, especially as activation levels increase, their average value is 15.72% activation, with a minimum value of 7.56% and a maximum value of 25.22%. Although this is not an indication that inter-subject differences should be taken lightly, it does indicate that their variation can be quantified, although no inferences about control of inter-individual differences can be taken at this point, since no other studies, to the author's knowledge, have looked at this important measure from this perspective.

Another interesting result of the EMG ANOVA corresponds to the Magnitude variable. Although expected to be significant (as it was), the overall expectance is for muscle activation levels for agonist muscles to be near the 50% mark when 50% exertions are performed and near the 90% mark when 90% exertions are performed. As can be seen in Figures 9 to 19, this was not the case. However, when the differences between the Magnitude levels for the agonist muscles in each exertion are calculated, some 40% differences do exist. The occurrence of the agonist activation differences, however, is not common enough to support the correct application of the loads.

Since further study of the disagreement between applied load magnitude and agonist activation magnitude was warranted, measured participants' MVE's were analyzed. The ANOVA for this dependent variable is shown in Table 9, and it was performed to determine if any of the factors that may have affected the collection process of MVE measures were significant. This was not the case, with the only significant variable being Direction (i.e. flexion, extension, lateral bending, or twist). Thus, any theory that the lower than expected activation levels were a result of differences between the MVE's on the first and second days is unsupported. Another explanation is that there are significant differences between the activation patterns when a person is performing a MVE, which might alter the normalization process. However, this hypothesis cannot be tested with the current data. A third possibility is simply that the peak EMG value (i.e. voltage) selected as the maximum is overshooting the true maximum. This effect might be mitigated by averaging values on a window of a predetermined width that covers the maximum EMG signal area of an MVE exertion. The magnitude of this EMG processing modification, however, would most likely be of limited impact, since peaks were taken at the maximum points in the signal that followed the usual ramp-up, peak, ramp-down effort, whose value would not be affected greatly by averaging around a small window centered at the maximum. For the current analysis, EMG MVE values were selected from the peak of the RMS waveform, while averages of the complete RMS waveform were calculated for resting and experimental conditions. While this process might introduce a mismatch in the data processing approaches used, it is not considered to considerably affect the resultant NEMG calculations, and has been used widely in the literature.

Previous studies (e.g. Kumar, 1996) have established MVE databases. To study the current data's feasibility, the MVE's obtained were compared against studies by Kumar (1996). The current averages of 151.0, 148.6, 72.93, and 39.62 Nm (flexion, extension, lateral bending, and twist, respectively) are for the most part lower than those in Kumar (1996, male and female average), 130, 206.5, 118.5, and 52.5 Nm. Several notable differences, however, do exist between the studies. In Kumar (1996), participants are seated, while they are standing here. The protocol in Kumar (1996) also allows for a wider variety of body heights and weights, with the possibility that their participants were stronger than participants here. The most troubling data point concerning MVE's in this study is the virtual equality of the flexion and extension MVE's. It was expected that extension MVE's would be significantly larger that flexion MVE's. One plausible explanation for the difference is that, when performing extension exertions, participants were able to look at the experimental setup they were pulling on, and might have been unconsciously restraining their effort out of fear of pulling anything out of the experimental apparatus.

A troubling result concerns the activation pattern for the lateral bending trials which appear to be too low for the loads applied. The most likely explanation for this effect is that participants were slightly adjusting their posture to allow vertical support of what was supposed to be primarily a horizontal force. Although posture was monitored by the experimenter and the participant was provided feedback regarding their position, there is certainly a possibility of occurrence of the situation. This is supported if another look is taken from the Lavender data (Figures 32-39). At this data point (90°), differences between the data sets become smaller. In some instances, the activation from the Lavender data set surpasses the activation currently measured.

Another interesting result meriting discussion is the significant difference between L3/L4 moments calculated from the force plate and L3/L4 moments calculated from the EMG data. The average (S.D.) errors among these measures across all loading conditions and subjects (with the muscle gain set at 30 N/cm^2) were 33.9 (10.5) Nm for the sagittal plane, 16.0 (8.6) Nm for the frontal plane, and 14.5 (7.4) Nm for the horizontal plane. Participant eight had considerably higher average errors than the others, with errors of 59.3 Nm, 28.3 Nm, and 27.9 Nm, for the sagittal, frontal, and horizontal planes, respectively. Upon examination of this participant's data, no particular source for the difference could be identified, and thus the data for this participant were not excluded from the analysis.

To further explore the effects of the main experimental factors on the error, an ANOVA analysis was performed. The magnitude of the error was significantly influenced by load magnitude (higher loads had larger errors, *p-value* $= 0.01$), moment type (see above, *p-value* $= 0.001$), and loading direction (*p-value* < 0.001). The loading direction factor merits further discussion at this point. Detailed observation of this factor uncovered that loading conditions which included applied flexion exhibited significantly higher error magnitudes than any of the other conditions. This indirectly supports the maximum muscle stress determination approach followed by Nussbaum and Chaffin (1998), that assigns separate muscle stress parameters to flexor and extensor muscles. The validity of the last statement, however, depends upon further examination and manipulation of the data with the purpose of determining whether error magnitude is decreased with this approach in this dataset as well. This finding, however, is not useful for error minimization for the present investigation, in which gain values could not be directly manipulated.

The errors described above are probably due to the combination of two factors. The first has been suggested before, and entails the gain parameter. Although it is accepted that this parameter varies between individuals and sets of muscles, such variability has not been incorporated into the models studied here. Thus, introducing gain values that are based on data obtained on any individual would affect each model's predictive ability, since it would require a data collection process before the model is used. The approach selected here was to use gain as a term to minimize *average* error between the force plate data and the EMG estimated data. Further study should center around the establishment of appropriate values for this parameter for the muscles in the lower torso area.

The second factor is the anatomy used. Even when the participant's height and weight were matched, people have different body sizes and shapes, which fixed average values for muscle moment arms and lines of action cannot accurately model. Errors caused by anatomical differences are combined as well with our simplification of the actual anatomy of the area, which consists of hundreds of muscles slips connected to different spinal sites, into only 14 different muscle groups. More study is needed in this area, both to determine the sensitivity of activation-force functions to anatomy changes, and to add inter-individual variability to available anatomical data.

5.2 Model Data Collection

No specific model outperformed the others across a majority of the tests completed. Thus, none of the models can be proclaimed winner nor any of them fulfill the requirements of the research question motivating this investigation. The performance of the ANN, DMH, and SCI models ranged from satisfactory to dismal depending on the test applied. Therefore, none of the models can be recommended, *at this stage of development*, as an "all-around" lumbar muscle pattern prediction tool. That said, it is still informative to examine in detail the results of the tests completed.

All coefficients of determination when the models were examined by their performance across muscles were lower than 0.88, with average coefficients of determination (R-square) for the particular models (when calculated per muscle) ranging from 0.36 to 0.40 (see Table 10). The best modeled muscle was the right multifidus, with an average coefficient of determination of 0.80. The right rectus abdominis had the second highest R-square value at 0.62. The right latissimus muscle was the worst modeled muscle, with an average R-square of 0.03. These results tend to be lower than equivalent data presented in other studies. However, this is expected, given the larger set of loading conditions considered here. The best performing models when average R-square values are taken across muscles are the SCI and DMH models (average R-square: 0.40), with the ANN model not far behind with a R-square of 0.36.

It is important to note in the results averaged by muscle that muscle data over all the loading conditions was used in the calculation of the parameters. It is possible, therefore, that a particularly bad performance in any condition might hurt overall muscle performance for any particular model. Therefore, coefficients of determination and coefficients of correlation were calculated for each model and loading condition (Table 11). Under this grouping situation, performance differences between the models were a bit more marked. The SCI model was the best performer (R-square: 0.45), followed by the DMH model (R-square: 0.37), and the ANN model (R-square: 0.23). The best performance was obtained in the applied extension loading condition, followed by the 90°-Sagittal/Horizontal (applied clockwise twisting) and the 45°-Frontal/Horizontal (applied lateral bending and clockwise twisting). Overall, model performance across loading conditions had a higher degree of uniformity than model performance across muscles. Sagittal/Frontal loading conditions, which comprise the majority of published studies, were on the average better modeled than more “complex” conditions (i.e. those involving axial twisting). However, the difference between “complex” and other conditions is not large enough to suggest a conclusion of better performance for any specific set of conditions. This finding is encouraging. A finding of better model performance for the Sagittal/Horizontal plane would have implied that models could be good predictors in that plane, but did not have the resources and/or correct technology to be useful predictors in other loading planes. Similar model performance between planes thus implies that the modeling technology may at least partly be in place. The low R-squares obtained, however, imply that adjustments in the modeling technology are still necessary to achieve satisfactory performance levels.

In the interest of thoroughness, performance of the models was assessed against each participant's data, grouped as well per muscle and per loading condition. R-square values remained similar to the results for pooled data, with average values across all muscles in the 0.40's (0.20's across loading conditions). The poorest performance per participant occurred for participants 2 and 7, which had shown some divergence from the norm in the activation patterns (see Figure 20). The experimental observations do not provide any clues as to possible causes of the differences, therefore, their data is kept, and their variation has to be regarded as a possible, albeit not common, variation between individuals.

Since R-square and correlation values appear not to differentiate between any of the models, pattern of activation graphs were developed (Figures 21 to 31) for the different loading conditions. The graphs confirmed the lack of fit between models and the activation patterns. However, the graphs show that the ANN and DMH models have the greatest lack of fit in the abdominal muscles, while the ANN models the back muscles closer. The activation levels of the abdominal muscles predicted by the ANN and DMH models are also particularly high, with the DMH predicting activation levels higher than 100% for these muscles in one loading condition. These models would certainly benefit from utilizing different (i.e. smaller) gain parameters in the flexor muscles, since lower gain values might help reduce the considerable amount of error for these muscles. The change in flexor muscle gains is certainly supported if the effect of loading direction on the moment agreement error is recalled. Larger errors were observed in loading conditions that primarily required the activation of flexor muscles.

Interestingly, if magnitude effects are taken aside, the patterns these models predict are close to what the actual pattern is. Again, this might indicate that the main source of error is in the gains selected or in the anatomy used. Recall the disagreement between the L3/L4 moments calculated from the force plate and the L3/L4 moments calculated from the EMG signal (*R-square: 0.19*). Significant differences were found among both. If the EMG signal cannot be directly manipulated (i.e. calculation of moments caused by muscles' activation) to produce a set of feasible moments, it is unlikely that models using the same anatomy and parameters will produce accurate patterns.

The effect of large errors in the magnitude of the muscles' activation is further noticed in the analysis of truth tables (Table 12). The truth table analysis establishes a better performance of the DMH model when muscles are active. It predicts a muscle active 64.82% of the time it actually is. However, the SCI and ANN models are better at predicting muscle silence, doing so correctly 76.61% and 87.84% of the time (threshold set at 5% activation). The better performance of the DMH model when predicting activity, however, might be in part caused by its over-prediction for many muscles; it tends to predict higher activation levels than were observed. The analysis, however, still makes a selection of the best difficult, since no particular model performed well on both active-active and silent-silent predictions.

Another criteria a model should comply with is to produce muscle activation patterns that become reaction moments that equilibrate the moments used as inputs to the model. Again, all models used here, ANN, DMH, and SCI, received a set of moments as their inputs, and returned a muscle activation pattern. Predictive reaction moments can be calculated from these patterns, from which an error can be calculated (when appropriately subtracted from the input moments). The average errors produced by the different models were shown in Table 13, with R-square values and correlation coefficients shown in Table 14. The largest errors occurred for the sagittal plane (average, 10.47 Nm), while the horizontal plane had the smallest (average, 8.69 Nm). The best performer in this criterion, as expected, was the SCI model (R-square, 1.00), since one of its constraints is that any solution it provides has to create a reactive moment equal to the input moment. The DMH model performed better that the ANN model in the sagittal and horizontal planes, with the ANN modeling the frontal plane more closely. The R-square and correlation values for the DMH model were also higher than the values obtained for the ANN model. Overall, however, and compared with the total moment amounts that were applied, moment equilibration errors were low, and do not point to any specific factors in the error minimization algorithms used by the models that might have influenced the results.

One of the most important aspects of muscle activation pattern modeling, at least from a practitioner's point of view, is the disc compression force predicted by any particular model. Table 15 showed the average compression forces per loading condition and magnitude predicted by each model and estimated from the EMG measure. The DMH model predicted the highest compression levels, but also the closest to those estimated from the EMG data (p-value, 0.95, no significant difference). The SCI and ANN models predicted forces significantly different (lower) from those estimated from the EMG data. Based on the EMG data, the highest compression occurred in the condition involving applied flexion and clockwise twisting (average across subjects, 2493 N), while the smallest compression occurred for the cases involving applied lateral bending and applied lateral bending with applied flexion. The compression values for the cases involving lateral bending, however, are affected by the low activation values obtained, which were discussed above.

Qualitatively speaking, ease of use and speed are also significant criteria when evaluating models of this type. If at any point in time any of these models is to be used in an application oriented environment, these criteria take on added importance. Based on the author's experiences with the models, SCI is easier to use than any of the other two, since it does not have as many adjustable parameters, other than those inherent to the optimization process. The DMH and ANN models have more parameters that can be adjusted to fine tune the model, which makes them harder to "tune" correctly. In terms of speed, however, the DMH model is better, since it doesn't require costly non-linear optimization operations (i.e. SCI), or a long training process (i.e. ANN). If the training process is obviated, however (a possibility since once the network is appropriately trained it can be used on an infinite number of occasions), then the ANN model is faster, since it only requires straightforward mathematical operations and no iteration process to minimize error.

Chapter 6. CONCLUSIONS

Although the lumbar region of the spine is the source of many occupational illnesses, significant in terms of their frequency, cost, and morbidity, the details of its physiological operation are still for the most part unknown. The costs of back pain have been placed on the order of tens of billions of dollars annually (NIOSH, 1997; Cats-Baril and Frymoyer, 1991; Frymoyer et al., 1983), with the associated costs including lost workdays, decreased productivity, personnel retraining and medical expenses, among others. These costs are distributed over a large number of cases, with some estimates placing its incidence as high as 50% of all reported musculoskeletal diseases (NIOSH, 1997; Praemer, et al., 1992).

In part as a result of these motivations, research on the spine, specially its lumbar region, has been performed over the last four decades. An important aspect of this research is the attempted modeling of the lumbar muscle activation patterns. The significance of this type of research resides in the possible key it holds to understanding the muscle activation patterns our body uses to counteract external loads that are transferred to the spine region. Once those activation patterns are at least understood, better attempts to establish injury mechanisms to the lumbar spine based solely on biomechanical factors can be made, especially for situations in which large loads are present.

There is still no single model in the scientific literature that, under a wide range of loading conditions, is able to predict lumbar muscle activation variability accurately enough. Thus, their current use as design tools available to ergonomic practitioners is limited, because the models are not well suited to handle the variety of tasks involving the use of the back that are present in occupational environments. Traditionally, the models used in this field are grouped between EMG based models and predictive models. EMG models take surface EMG signals and translate them to muscle forces that counteract the applied spinal load. Predictive models attempt to approximate the neural control structures used by the human motor control system through the use of mathematical functions, outputting predicted muscle activation patterns. Although each technique has pros and cons, both are hindered by the fact that no direct validation is possible at the present.

Testing of these models is also hindered by the limited data available on surface EMG of the lumbar muscles when resisting combined frontal, sagittal, and horizontal moments.

Although data is available on combined frontal and sagittal loading, horizontal (twisting) moments are seldom considered. Even when they are considered, they are not systematically varied. Furthermore, available data seldom includes inter- or intra- subjects variability measures, and the experiments collecting the data used fixed loads, with little, if any, regard for the normalization of those loads against the participant's MVE's.

Despite these drawbacks, in the recent biomechanics literature several predictive models have been created and/or updated which show promise in terms of their performance and simplicity of use (ANN's, DMH, and SCI). They use physiologically valid parameters, and, to varying degrees, have associated physiological processes to which they relate. Their reported performance levels support the idea of looking further in the operation of these models to obtain possible clues about the behaviors our body follows in lumbar muscle recruitment.

This process, however, should be preceded by a through comparison of the model's performance. Such a comparison is performed in this manuscript. In order to perform the comparison, surface EMG data of several trunk muscles were collected, while attempting to address the drawbacks of current data that were outlined before.

The dataset of lumbar muscle activation patterns obtained is comparable to some datasets collected before in pattern shape, but adds to them patterns arising out of higher load levels. It also adds to the literature the patterns of activation for a wider set of moment combinations in the three axes of three-dimensional motions. There appears to be considerable variability in the way different individuals recruit the lumbar muscles studied, even though considerable efforts were employed in using participants similar in height and weight, and in normalizing the loads applied. Variation within specific individuals was small enough to remain non-significant.

It is important to keep in mind that whenever EMG data is collected, several potential problems exist, which might be present in the current dataset. First, the EMG data is normalized against the activation levels obtained in MVE exertions. Several problems exist with MVE exertions. Since they are voluntary, they are directly dependent on the participants will to do them. This "desire" might change from day to day, or even from exertion to exertion. To mitigate this effect in the current investigation, the number of MVE's required were kept to a minimum and performed at the beginning of the session. Practice is also necessary in order to learn to perform MVE's correctly. Although practice was provided in the current experimental protocol, participants were by no means experts in performing them after completing the experiment. The main effect of wrong MVE values would be inaccuracies in the activation levels reported.

Second, the issue of selecting a voltage value from any MVE EMG spectrum represents a potential trouble source. Different researchers select this value differently, and their choice is not always apparent. Among the options available in the selection of this parameter are to select solely the maximum voltage value in the spectrum, to average values across a small window centered at the peak, or to use a filtering scheme across the curve and then pick the resultant peak (point of zero tangent). In the current research, the first alternative was selected, taking care to ensure that the peak selected was part of the MVE. The selection of this alternative might have driven activation levels down somewhat, at least keeping them lower than the values expected.

Electrode cross-talk is a third potential problem with the data collected. Any surface electrode used might pick signals not only from the muscle of interest, but from nearby muscles as well. Although it is currently impossible to eliminate this effect completely, its effect can be mitigated by measuring muscle activation levels resulting from functional exertions before the actual data is collected. Functional exertions were, to a limited extent, part of the experimental protocol followed here. Electrode cross-talk can also be minimized with the use of indwelling electrodes, but their use was not considered here due to the complexity they add to the experimental protocol.

The models' provided poor predictions against the dataset collected. However, they did demonstrate limited predictive ability on a set of loading conditions that included systematically varied axial moments. The difference between measured and estimated L3/L4 moments (when using force plate data against EMG data), combined with the observation regarding the match in patterns of activation, suggests that the models' performance was largely and adversely affected by the physiological parameters selected (i.e. anatomy and gain).

It is quite impressive, despite the model's performance, how a set of three models that are based on completely different technologies and underlying assumptions can predict patterns that are as close to each other. Although points where the model predictions' differ do indeed exist, those points in which they do not differ are the most puzzling. How can this be the case? How can completely different algorithms, implementing completely different approaches, be so similar in the way they distribute the loads to the torso? Part of the answer does lie in the fact that these models were built with the purpose of simulating existing data as closely as possible.

However, the fact that their performance has proven to be similar across loading conditions fundamentally different from those they were intended to simulate is certainly puzzling.

Based on the analysis performed in this work, *no model can be proclaimed a better performer*. It is clear, however, that further work is needed in this area before we are able to accurately predict arbitrary lumbar muscle activation patterns from sets of three-dimensional moments. The use of these models to make engineering decisions, although possible, should at this point be cautious. Although some models predicted considerably well the activation of *specific* muscles or loading conditions, none of the models performed *consistently* well.

Future research in this area should follow several compatible but fundamentally different directions. It seems we have three distinct possibilities for sources of error. The first is the chance that the theory behind the models is faulty. Researchers following this line of thinking should strive to develop new models that simulate more closely the dataset presented here and future datasets that become available. The author feels, however, that the models evaluated here can certainly be improved, which introduces the second possible source of error: parameters in the models have to be adjusted.

Adjustment of parameters in the models has to be systematically studied to determine their effects on model predictions. Although a trial and error approach can be used, a more efficient approach is to perform sensitivity analysis on the parameters. A model parameter deserving special consideration is the anatomy used in the model. The human modeling field, especially that related to the lumbar muscles, needs detailed anatomical models that not only provide averages, but standard deviations, and that associates muscle parameters with anthropometric data.

The third source of error is the data itself. There is certainly a distinct possibility that the measures under study are not appropriate for the applications under study. There is also the significant number of error sources the EMG signal itself can be affected by, which has been discussed before. Certainly as data capturing technology improves (e.g. sampling rates, number of channels sampled, noise) researchers are able to extract more out of each measure under study. Perhaps it’s time to start focusing on some other aspect of the signals we collect.

In the long term, comparison efforts such as the one described here and others that include dynamic conditions should result in the improvement of models, with the ensuing benefit of an improved understanding on the behaviors of the human brain in muscle recruitment patterns. This understanding will complement the concurrent developments on the mechanisms involved in lumbar injuries, which directly translates into the better design of occupational tasks that stress the low back.

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APPENDIX A:

INFORMED CONSENT PACKAGE

Appendix A – IRB Approval Package

REQUEST FOR APPROVAL OF INVESTIGATION INVOLVING HUMAN SUBJECTS

Investigator(s): Miguel A. Perez and Dr. Maury Nussbaum, Faculty Advisor

Department: Industrial and Systems Engineering

Project Title: A Comparison Between Predictive Models of Torso Muscle Recruitment Patterns

Source of Support: Departmental Research ☑ Sponsored Research ☐ Proposal No. ______________________________

1. The criteria for "expedited review" by the Institutional Review Board for a project involving the use of human subjects and with minimal risk is one or more of the following. Please initial all applicable conditions and provide a substantiating statement of protocol.

☐ a. Collection of:
1) hair or nail clipping in a non-disfiguring manner;
2) deciduous teeth;
3) permanent teeth if patient care indicates need of extraction.

☐ b. Collection of excreta and external secretions: sweat, uncanulated saliva, placenta removed at delivery, amniotic fluid obtained at time of rupture of the membrane.

☑ c. Recording of data from subjects 18 years or older, using non-invasive procedures routinely employed in clinical practice. Exemption does not include exposure to electromagnetic radiation outside the visible range.

☐ d. Collection of blood samples by venipuncture (not exceeding 150 ml/8 week period, and no more than twice a week) from subjects 18 years or older, in good health and not pregnant.

☐ e. Collection of supra- and subgingival dental plaque and calculus, provided the procedure is no more invasive than routine sealing of the teeth.

☐ f. Voice readings.

☑ g. Moderate exercise by healthy volunteers.

☐ h. Study of existing data, documents, records, pathological specimens or diagnostic specimens.

☐ i. Research on drugs or devices for which an investigational exemption is not required.

2. If the project involves human subjects who are exposed to "more than minimal risk" and are not covered by the criteria above (a to i), the IRB review must involve the full IRB board. Please check if the research involves more than minimal risk** __ and provide a substantiating statement of protocol.

3. Human subjects would be involved in the proposed activity as either: Minors and/or Children*___, Fetuses___, Abortuses___,Pregnant Women___, Prisoners___, Mentally Retarded___, MentallyDisabled___.

Note that if children are involved in the research as human subjects, they may have to provide consent as well as their parents.
Whether or not the project may undergo "expedited review" or must be reviewed by the full Institutional Review Board, it is necessary that the required informed consent forms also be reviewed. These should be submitted with the proposal. However, if there is insufficient time to meet the sponsor's deadline, submittal can be delayed up to thirty days after submittal of the proposal without jeopardizing the IRB certification to the prospective sponsor.

*Minimal risk means that the risks of harm anticipated in the proposed research are not greater, considering the probability and magnitude, than those encountered in daily life or during performance of routine physical or psychological examinations or tests.

**Subject at risk is an individual who may be exposed to the possibility of injury as a consequence of participation as a subject in any research, development or related activity which departs from the application of those established and accepted methods necessary to meet his needs, or which increases the ordinary risks of daily life, including the recognized risks inherent in a chosen occupation or field of science.
This is to certify that the project identified above will be carried out as approved by the Human Subject Review Board and will neither be modified nor carried out beyond the period approved below without express review and approval by the Board.

____
Investigator(s)/Date

The Human Subjects Review Board has reviewed the protocol identified above, as it involves human subjects, and hereby approves the conduct of the project for ____months, at which time the protocol must be resubmitted for approval to continue.

____
Departmental Reviewer/Date

____
Chair, Institutional Review Board /Date

Justification of Project

Back pain is a very frequent disease in the American workforce. It is one of the most common occupational diseases, with billions of dollars in associated annual costs. Researchers on this area, despite significant efforts, have not yet been able to understand completely the complex operation of the human spine. The most common tools used for this purpose are predictive modeling techniques. These techniques take a particular loading situation to which the body is exposed and attempt to simulate the way lumbar muscles are activated to counteract the external load. Three recently published models of the predictive type will be compared in this thesis. The results should allow a better understanding of these models and a determination of their levels of performance under different loading conditions. The physiological data collected from the participants of the study will also contribute to the field by addressing drawbacks of data that are currently available.

Procedures

Participants will be recruited from a university student population. A total of 16 participants will be used, with an equal number of male and female participants. The participants will report for the experimental sessions at the Industrial Ergonomics Laboratory, in the fifth floor of the Whittemore building. Participants will read an informed consent form and sign it if they agree to participate in the experiment. Afterwards, they will fill out a health questionnaire (attached at the end of this package) and their height and weight will be measured. These two items will be used as screening tools. If the participants are eligible to participate, they will be instrumented with bipolar surface electrodes to obtain electromyography signals from some of their muscles. After the electrodes have been placed and tested, participants will perform a series of Maximum Voluntary Exertions (MVE) which involve the voluntary maximal activation of different sets of muscles. Participants will then be secured to the data collection apparatus (please see Figure 1) and will start performing the experimental treatments, with rest periods between treatments, as instructed by the experimenter. Once the experimental treatments are finished, they will be compensated for the time spent in the experiment The process described here should take an average of three hours, over two different days (one hour the first day, two hours the second day).

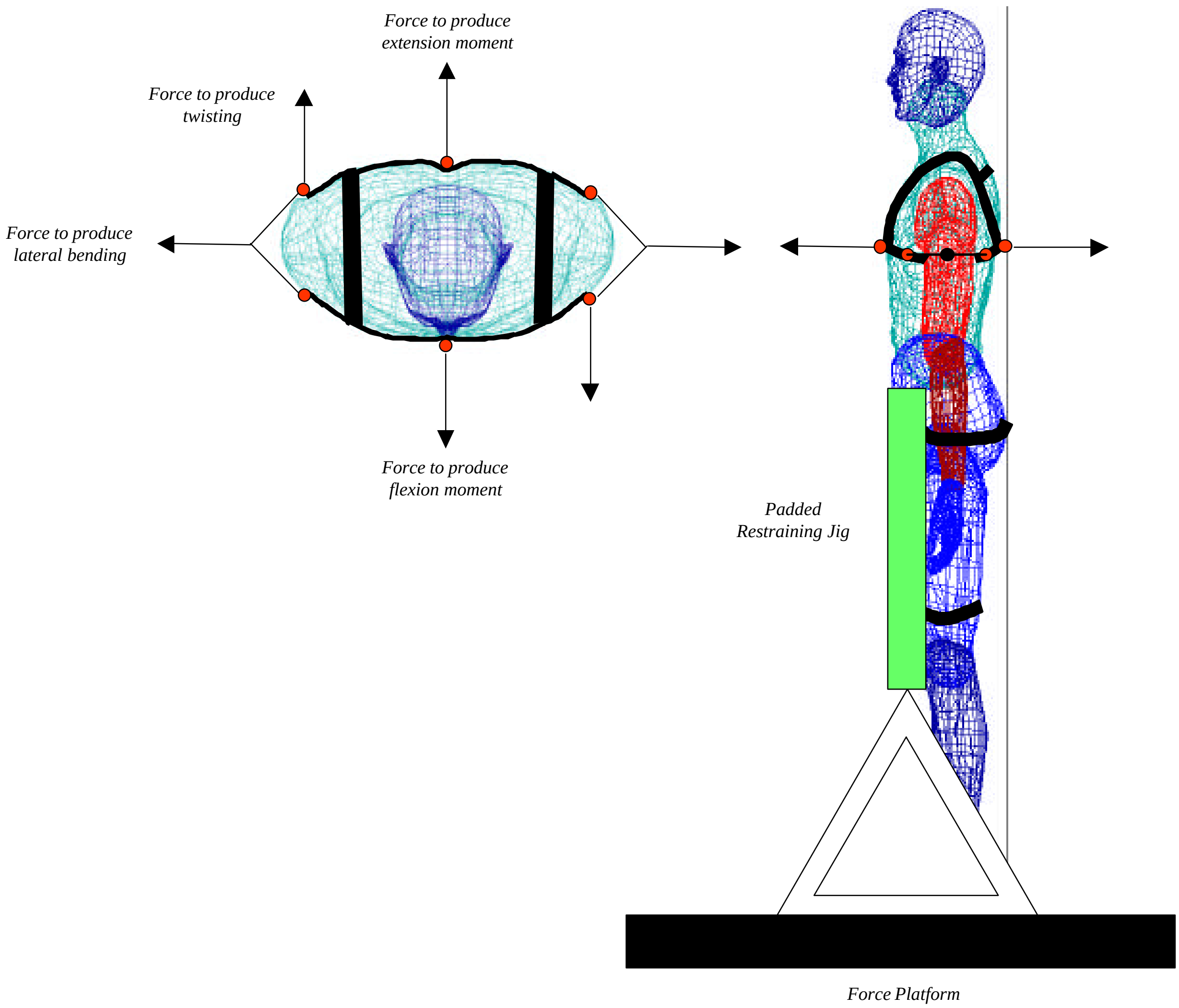

Figure 1. Data Collection Apparatus

Risks and Benefits

This experiment should pose only minimal risks to participants. The experimental tasks are not a cardiovascular threat, and the measures taken are not invasive in any way. There is a small chance that participants may experience some back pain due to the use of this body part in the experimental trials. The risk of this happening, however, is no more than the normal risk they would experience while performing normal activities. If pain does develop, participants will be instructed to stop their participation and withdraw from the experiment. They would be referred to the proper physicians in the University.

There is also a slight chance that some participants may experience some delayed muscle soreness similar to that produced by physical exercise. Some people may also have an allergic reaction to the adhesive used in the electrodes. However, the Industrial Ergonomics lab at Virginia Tech (i.e. where the experiment will be conducted) has employed similar procedures as those described here in the past with no adverse effects.

Benefits of this research were outlined before, but, in summary, we expect to gain a better understanding of the models evaluated, a determination of their levels of performance under different loading conditions, and to produce a comprehensive database of lumbar muscle activation patterns that can be used in future research. The researchers consider that, given the minimal risks associated with this type of experiment, they are outweighed by the benefits. The subjects may benefit from the understanding that they are helping to augment our knowledge of the low back behavior, which should translate in the future to a lower incidence of diseases affecting this region in occupational sectors. However, no direct or implied benefits, other than the monetary compensation they will receive, are proposed to the participants to secure their participation.

Informed Consent

The informed consent form follows this document.

Anonymity

During the course of this experiment, the participant's anonymity is guaranteed. No videotape equipment will be used. All data collected during the course of the experiment will be identified via a code. For data collection purposes, only the experimenter will know the relationship between that code and the participant's identity. Once the participant has finished their participation, any existing evidence of this relationship will be destroyed, and the data collected from the participant will only be referred to by using the code.

Biographical Sketch

The experimenter, Miguel A. Perez, is currently a Master's level student in the Industrial & Systems Engineering Department. This is his second year of study in the Master's program. He has a Bachelor's degree in Industrial Engineering from the University of Puerto Rico – Mayaguez campus. Through different courses, he has been exposed to the ethics of human research and the proper research methods used in the Human Factors field. He has also served as assistant to a number of experiments conducted in the University. Miguel is a member of the Phi Kappa Phi, Alpha Pi Mu, and Tau Beta Pi Honor Societies. He is also an active member of several other professional organizations.

The Faculty Advisor, Dr. Maury Nussbaum, is an Assistant Professor in the Industrial & Systems Engineering Department and Director of the Industrial Ergonomics Laboratory at Virginia Tech. He obtained his graduate and undergraduate degrees in the University of Michigan. Dr. Nussbaum has more than 8 years of experience in ergonomics and biomechanics research, with numerous publications in these fields and current direct involvement in several research projects, in some of which he serves as the Principal Investigator. He is currently a member of the Institutional Review Board (IRB) that examines proposed research in the University for compliance with the standards of protection to participants.

Appendix A – IRB Approval Package

VIRGINIA POLYTECHNIC INSTITUTE AND STATE UNIVERSITY

Informed Consent for Participants
of Investigative Projects

Title of Project: A Comparison Between Predictive Models of Torso Muscle Recruitment Patterns

Investigator(s): Miguel A. Perez and Dr. Maury Nussbaum, Faculty Advisor

I. The Purpose of this Research/Project

The purpose of this research is to obtain data to compare models that predict the muscle activation patterns in the low back. This comparison should, in the long run, yield better models that allow researchers to better understand the low back and to prevent its injury. There will be a total of 16 participants in this study.

II. Procedures

You will read this form and sign it if you agree to participate in the experiment. Afterwards, should you decide to participate, you will fill out a health questionnaire and your height and weight will be measured. If you are found eligible to participate in the experiment, you will follow these steps:

1. You will have electrodes placed on several muscles, which control your low back movements. These electrodes are used to collect information from muscles indicating their activation levels. The procedure for attaching these electrodes involves cleansing a small patch of skin over the muscle area. The electrodes are then placed on the skin and remain in place with a safe adhesive.
2. You will be asked to wear clothing that allows placement of the electrodes on the bare skin.
3. The investigator will then demonstrate several muscle exertions you will then perform. During these exertions you should try to develop as much force as you can against the resistance provided.

4. The investigator will then explain the different treatments you will participate in, and the way the experimental apparatus works.
5. You will be secured to the experimental apparatus as tightly as possible without causing you discomfort.
6. You will perform a series of trunk exertions, in which you will be instructed, and asked resist a series of loads applied to your trunk through the experimental apparatus.

The process described here should take an average of three hours, over two different days (one hour the first day, two hours the second day).

III. Risks

This experiment should pose only minimal risks to you. The experimental tasks will not require prolonged exertions, and the measures taken are not invasive in any way. There is a small chance that you may experience some back pain due to the use of this body part in the experimental trials. The risk of this happening, however, is no more than the normal risk you would experience while exercising. If pain does develop, you will be instructed to stop your participation and withdraw from the experiment. You will be referred to the proper physicians in the University.

There is also a slight chance that you may experience some discomfort related to the use of some muscles. Some people may also have an allergic reaction to the adhesive used in the electrodes.

IV. Benefits of this Project

Your participation in this study will provide information that will be used to develop better models of the low back. These models may one day allow researchers to precisely understand the way the human back works and, thus, to effectively prevent its injury. It will also serve as the basis for the research project I'm required to develop to obtain a Master's degree in Industrial Engineering at Virginia Tech.

V. Extent of Anonymity and Confidentiality

During the course of this experiment, your anonymity is guaranteed. No videotape equipment will be used. All data collected during the course of the experiment will be identified via a code. For data collection purposes, only the experimenter will know the relationship between that code and your identity. Once you have finished your participation, any existing evidence of this relationship will be destroyed, and the data collected from you will only be referred to by using the code.

VI. Compensation

You will be compensated at a fixed rate of five dollars per hour after each experimental session you participate in. If your participation extends over a fraction of one hour, you will be paid half the hourly amount for less than half an hour, and the complete hourly rate for any fraction greater than half an hour.

VII. Freedom to Withdraw

You are free to withdraw from this study at any time without penalty. If you choose to withdraw, you will be compensated for the portion of the time of the study you participated in. You are free not to answer any questions or respond to experimental situations that you choose without penalty.

If for any circumstance the experimenter determines you should not continue to participate, you will still be compensated for your time accordingly.

VIII. Approval of Research

This research project has been approved, as required, by the Institutional Review Board for Research Involving Human Subjects and by the Department of Industrial & Systems Engineering at Virginia Polytechnic Institute and State University.

IX. Participant's Responsibilities

I voluntarily agree to participate in this study. I have the following responsibilities: report any discomfort or pain to the experimenter immediately, perform all tasks to the best of my ability if I choose to perform them, and answer all questions asked by the experimenter to the best of my knowledge, if I choose to answer them.

X. Subject's Permission

I have read and understand the Informed Consent and conditions of this project. I have had all my questions answered. I hereby acknowledge the above and give my voluntary consent for participation in this project.

If I participate, I may withdraw at any time without penalty. I agree to abide by the rules of this project.

____________________________________ ________________

Signature Date

Should I have any questions about this research or its conduct, I may contact:

Miguel A. Perez (540) 552-5695
Investigator

Dr. Maury Nussbaum (540) 231-6053
Faculty Advisor

H. T. Hurd (540) 231-5281
Chair, IRB
Research Division

APPENDIX B:

PARTICIPANT SCREENING QUESTIONNAIRE

Participant Screening Questionnaire

Name: ____

Telephone: _____________________________________

E-mail: _____________________________________

Gender: ____________ *Date of Birth:* __________________

Height: ____________

Weight: ____________

Please answer Yes or No to the following questions:

1. Have you ever had a hernia? ____________
2. Have you had a back injury or back or spine operation? ____________
3. Have you had any noticeable back pain during the last year? ____________
4. Have you had any joint dislocations, broken bones, or other physical injuries in the last year? _________
5. Have you had any serious musculoskeletal injury? ____________

____

Signature and Date

Miguel A. Perez
1105 Lora Lane NW
Blacksburg, VA 24060
(540) 552-5695, mperez@vt.edu

VITA

EDUCATION:

08/97 - Present Virginia Polytechnic Institute and State University, Blacksburg, VA
Ph.D., HUMAN FACTORS ENGINEERING
Degree expected: *May 2002*
MS, HUMAN FACTORS ENGINEERING
Degree expected: *October 1999*
GPA: 3.94

08/92 - 12/96 University of Puerto Rico - Mayaguez campus, Mayaguez, PR
BS, INDUSTRIAL ENGINEERING
Degree: *December 1996*
GPA: 3.98

POSITIONS HELD IN COLLEGE:

08/97 - Present Virginia Polytechnic Institute and State University, Blacksburg, VA
GRADUATE TEACHING ASSISTANT
Responsible for all homework grading for Industrial Engineering's undergraduate and graduate courses. Clarify students' questions concerning engineering design problems or lecture material. Full responsibility for lectures (on different topics) in which the course instructor could not attend.

03/94 - 07/95 U. of Puerto Rico - Mayaguez: Solar Car Project, Mayaguez, PR
TEAM CAPTAIN
Managed a group of eight people during the design and manufacturing stages of the project. Directed all project related activities including work programming, design supervision and approval, fund raising, and deadline placement. Delegated responsibilities on fellow team members. The team exceeded expectations during my leadership, improving its position by more than 50 percent, compared with previous races.

PROFESSIONAL EXPERIENCE:

05/99 – 08/99 Engineering Animation, Inc., Ann Arbor, MI
SOFTWARE ENGINEER - INTERN
Improved modeling techniques used in the corporation's Jack™ software, used to model the behavior of "virtual humans" in a variety of user-defined situations. Improvements dealt primarily with the spine (lumbar, thoracic, and cervical) and shoulder areas of the "virtual human." The suggested modifications were based on data collected from the scientific literature. Developed code for the implementation of the CAESAR anthropometric database into Jack™.

08/98 Titmus Optical, Petersburg, VA
ERGONOMICS CONSULTANT
Conducted an ergonomic audit in the manufacturing floor of a 300+ employees company. Suggested improvements to then current workstations and manufacturing problems. The suggestions resulted in the creation of "operator-friendly" workstations and reduced the probability of product damage.

07/96 – 06/97 Techno Plastics Industries, Añasco, PR
PROJECTS ENGINEER
Performed operations analysis for all activities in the factory, including inventory planning and control, quality control, materials handling, and safety. Developed corrective measures for faulty items. Trained operators in the above areas. Developed layout for plant expansion already in progress.

RESEARCH EXPERIENCE:

08/98-Present Virginia Tech, Blacksburg, VA
THESIS RESEARCH
Developed ongoing research efforts to increment scientific knowledge of the lumbar area of the spine. The thesis intends to develop a comprehensive database on lumbar muscle recruitment patterns in static postures and empirically evaluate several modeling efforts of lumbar muscle recruitment patterns available in the literature. Responsible for the design and construction of the apparatus, the selection and installation of data collection equipment, and the conduction of the experiment.

MEMBERSHIPS:

- Alpha Pi Mu, *Puerto Rico Alpha Chapter*: *05/95 – Present*
  President *12/95 - 12/96*
- Tau Beta Pi, *Puerto Rico Alpha Chapter*: *08/95 - Present*
- Phi Kappa Phi, *Virginia Tech Chapter*: *05/96 - Present*

- Golden Key National Honor Society, *PR Chapter*: *05/96 - Present*
- Human Factors and Ergonomics Society: *08/97 – Present*
- American Industrial Hygienists Association: *12/97 - Present*

HONORS:

- National Research Council – Ford Foundation Fellow: *08/99 – 05/02*
- Outstanding Graduate Teaching Assistant: *05/99*
- Virginia Tech's Graduate Dean's Assistantship: *08/97 - 06/99*
- Frederick W. Taylor Award for Best Graduating IE Student: *06/97*
- Hispanic Scholarship Fund Scholar: *05/96 – Present (annual)*
- IIE, A.O. Putnam Memorial Scholarship: *05/96*
- Distinguished Student, PR Society of Professional Engineers: *05/96*