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A fuzzy relational rule network modeling of electromyographical activity of trunk muscles in manual lifting based on trunk angels, moments, pelvic tilt and rotation angles

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Abstract

The main objective of the study was to model the electromyographic (EMG) responses for 10 trunk muscles in manual-lifting tasks using the fuzzy relational rule network (FRRN). The FRRN utilized trunk-related variables, including sagittal and lateral trunk moments, pelvic tilt and pelvic rotation angles, and sagittal, lateral, and twist trunk angles as model inputs. The EMG data for model training and testing were randomly selected from a set collected for 20 college students. The data represented a total of 24 combinations of weight lifted (15, 30, 50 lbs), asymmetry (0°, 60°), and the origin and destination of lift (floor-waist, floor-102 cm, knee-waist, knee-102 cm), with two replications of each condition. The primary data-driven fuzzy model with relational input partition was trained using the laboratory EMG data for 10 subjects, and was then tested based on the EMG data for another 10 subjects. The model allowed for estimating EMG responses for the 10 trunk muscles with the average value of mean absolute error (MAE) of 9.9% (SD = 1.44%). This study demonstrates that application of fuzzy modeling techniques allows for estimating time domain EMG responses of trunk muscles due to manual lifting under limited task conditions.

Relevance to industry

Estimation of EMG responses using the proposed fuzzy-based system opens new opportunities for biomechanical modeling of manual-lifting tasks aimed at prevention of low back disorders at the workplace.

Keywords: Manual lifting; Electromyography; Trunk muscles; Model estimation; Manual lifting; Fuzzy relational rule; Soft computing

1. Introduction

Both epidemiological and biomechanical studies have demonstrated a link between the risk of the low back disorders (LBDs) and occupational conditions. Specifically, manual materials-handling (MMH) tasks are associated with greater risk of the LBDs. Marras (1992) documented workplace and individual characteristics to be highly related to LBDs risk. These factors included (1) lifting frequency, (2) load moment, (3) trunk lateral velocity, (4) trunk twisting velocity, and (5) the trunk sagittal angle. Biomechanical models have been developed to describe how the external and internal forces imposed on the body combine to load the spine during manual lifting (Marras and Granata, 1995). These models often use as inputs the electromyographic (EMG) data as muscle activity featuring the internal behavior of the body is usually described with EMG signals. Therefore, many biomechanical models heavily rely on the EMG inputs to

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'drive' them. Marras and Sommerich (1991) developed an EMG-driven dynamic three-dimensional motion model to examine trunk muscle activity patterns and to quantify biomechanical stresses on the spine during the isokinetic trunk-lifting exertion.

However, due to work environment conditions, it is often impractical or impossible to collect quality EMG data at various industrial or office sites. Typically, laboratory experiments are performed under precisely controlled conditions in order to measure muscle activity during the specific trunk motions. Therefore, laboratory-based biomechanical models, which utilize common laboratory instruments (EMG, dynamometers, etc.), are intended only for use under controlled conditions (Marras and Sommerich, 1991).

2. Objectives

Electromyography can be used as a measure of muscle tension for estimating the amount of muscle activity and evaluating task performance. As discussed by Lee et al. (2003), the EMG data are often needed as inputs for the "EMG-driven" and "optimization-based" biomechanics models. However, it is often impractical to collect EMG activity in industry, for example due to hostility of work environment or requirements of the production process. Laboratory experiments are, therefore, performed under precisely controlled conditions to measure muscle activity during the specific trunk motions.

The main objective of the present study was to estimate the EMG activities (expressed in time domain) for 10 trunk muscles due to manual lifting tasks using the soft computing methodology of fuzzy relational rule network (FRRN). The proposed model utilizes trunk moments, and trunk and pelvic angles as input variables. Fig. 1 below illustrates the overall structure of the developed model.

3. Soft computing techniques

3.1. Fuzzy logic

In the last 15 years, fuzzy systems that apply fuzzy logic for pattern recognition and approximate information processing and artificial neural networks have been used in variety of areas, including process control, engineering, management, business, medical diagnosis, biomechanics, human factors and cognitive simulations (Karwowski and Ayoub, 1984; Karwowski et al., 1984; Karwowski, 1985; Karwowski and Mital, 1986; Karwowski et al., 1987; Karwowski et al., 1999). Fuzzy logic that utilizes *if–then rules* (Zadeh, 1975a–c, 1994; Karwowski, 1992) provide a mathematical framework that allows to model the uncertainties associated with approximate reasoning, especially for the control systems where mathematical models are difficult to derive, including human perceptual and cognitive processes (information processing). For example, Jacobs (1997) developed a fuzzy logic-based control model of human stance that utilizes linguistic descriptors of muscular activation (i.e. large, medium, small, demonstrating that the human nervous system simplifies the control of movement in terms of global variables.

3.2. Artificial neural systems

Artificial neural systems are simplified mathematical models of the brain-like systems that function as parallel-distributed computing networks that can be trained to learn new associations, functional dependencies and new patterns (Zurada, 1992; Lin and Lee, 1996; Fuller, 2000). Artificial neural networks (NN) are adaptive, that is can automatically adjust (their weights) to modify their behavior in response to nonlinear dynamics of their environment. Over the last few years, NN have been successfully applied in medicine and biomedical studies, including research on the amino acid sequencing, reactions

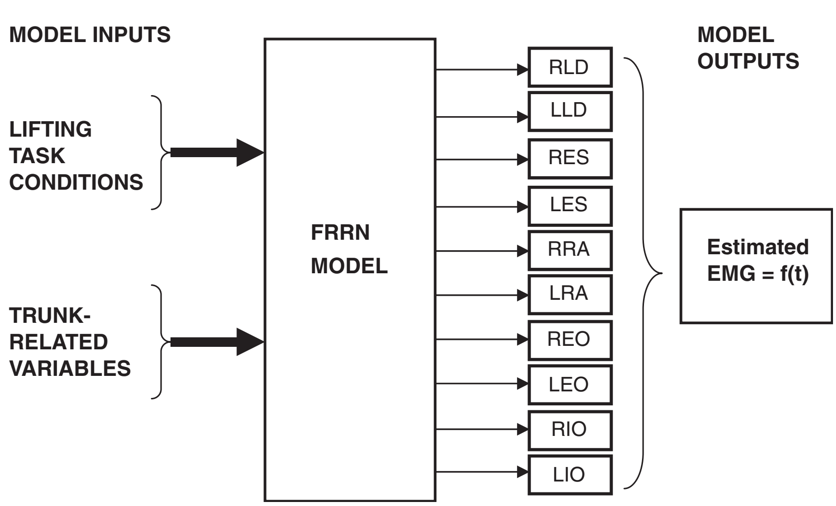

Fig. 1. The FRRN-based EMG estimation model structure.

to drug treatments, lung disease, cancer screening, classification of medical images, clinical diagnosis low back pain, and classification of low back injury (Zurada et al., 1997).

3.3. A neuro-fuzzy modeling and hybrid systems

While fuzzy logic allows for an inference mechanism under uncertainty, NN affords system learning, adaptation, parallelizm of information processing and generalization over time. A hybrid system, called a neuro-fuzzy system, which combines the concepts of fuzzy logic and NN (Lin and Lee, 1996; Fuller, 2000) enables development of the more human-like representations of the nonlinear biological and technological systems, including human neuromuscular dynamics and cognitive behaviors (Zurada et al., 1997; Jacobs, 1997). The behavior of fuzzy systems can be explained based on the fuzzy rules (of implication), but in general the new knowledge acquisition is difficult. NN can automatically acquire new knowledge through the well-defined algorithms and extraction of fuzzy rules form numerical data (Hou et al., 2005). NN are often used to tune membership functions of fuzzy control systems. A hybrid, fuzzy NN, is a network with fuzzy signals and/or fuzzy weights (Fuller, 2000). Such a system and can approximate any continuous fuzzy function in a specific domain and are capable of self-learning and self-organizing in a real-time, under the conditions of changes that occur in a multitude of relevant variables.

4. Soft computing studies of muscular exertions

The existing body of literature shows a number of studies that utilized soft computing techniques, such as, fuzzy logic, NN and genetic algorithm for the classification, pattern recognition, to study different aspects of muscular exertions. Chauvet et al. (2003), in their study, proposed an iterative classification algorithm using fuzzy-logic techniques. The classification method would allow automatic decomposition of EMG signals into their constituent motor unit action potentials (MUAPs). The method was utilized on six groups of 20 simulated EMG signals with a maximum and an average mean error rate of 2.13% and 1.37%, respectively. The study also utilized the proposed method on real surface EMG signals ranged from 10% to 40% of the maximum voluntary contraction. The algorithm was able to detect correctly detect 21 MUAPs, compared to 29 MUAPs detected by human expert. The method was found to be efficient and attractive for noninvasive muscle activity investigation.

Chan et al. (2000) used a fuzzy approach for the classification of EMG signals for prosthesis control. In this study, the EMG signals were divided into several time segments in order to maintain data pattern structure. The study utilized a trainable fuzzy system that used an unsupervised algorithm for clustering that data. The clustering results were then used in initializing the fuzzy system parameters. Then, fuzzy rules in the system were trained with the back-propagation algorithm. In the study, the fuzzy system was compared with an artificial NN method. Both the methods obtained similar results. However, the fuzzy approach was considered superior with respect to recognition rate, sensitivity to overtraining, and consistent output.

In their study, Hussein and Granat (2002) proposed for a neuro-fuzzy EMG classifier for the intention detection of the patient. In this study, following use of a Gabor Matching Pursuit (GMP) and genetic algorithms for feature extraction, an adaptive neuro-fuzzy inference system (ANFIS) to classify the EMG signals. The study used 30 standing up and 30 sitting down EMG signals with seven-bell membership function and 30 rules. It was found that the neuro-fuzzy classifier was able to correctly identify 29 standing and 28 sitting EMG signals out of 30 signals, respectively. The negative false classification was 1 and 2 for standing and sitting positions, respectively. Therefore, the study proved the neuro-fuzzy classifier as a highly sensitive and specific classification scheme.

Micera et al. (1999) utilized a hybrid approach to EMG pattern analysis for classification of arm movements. The hybrid model included generalized likelihood ratio (GLR) test, the principal component analysis (PCA), autoregressive (AR) parametric modeling, and cepstral analysis with Abe-Lan fuzzy classification approach. The study included EMG signals of superior trapezius, anterior deltoid, and pectoralis major during sagittal, contralateral, and ipsilateral pointing with the arm. The study found the classification method to correctly classify all the EMG patterns related to the selected planar arm pointing movements. Micera et al. (2000), in a similar study, reported use of self-organizing maps (SOM), fuzzy c-means (FCM), multilayer perceptrons (MLP), and the Abe-Lan fuzzy network in classifying those three muscles in the same arm pointing task (see Micera et al., 1999). The study found the range of classification accuracy (percent) as 47–53, 50–57, 83–87, and 90–97 for SOM, FCM, MLP, and Abe-Lan method, respectively.

Lee et al. (2003) developed a neuro-fuzzy model for predicting peak EMG values for trunk muscles based on lifting task variables. The model utilized two task variables, i.e. trunk moment and trunk velocity, as inputs, and 10-muscle activities as outputs. The input and output variables were represented using the fuzzy membership functions. Initial fuzzy rules were generated by NN using true EMG data. The final fuzzy rules were used to derive the prediction model. The model was developed based on EMG data for 8 subjects, and validated using the EMG data for another 4 subjects. The model allowed to estimate the normalized peak EMG values only with the mean absolute error (MAE) ranging from 4.97% to 13.16% (average = 8.43%; SD = 2.87%), and average value of the mean absolute difference between the real and estimated EMG of 6.4% (SD = 3.39%). The authors concluded that estimation of EMG responses in manual lifting tasks is feasible, and that model performance could be improved by increasing the number of input variables.

5. Methods and procedures

5.1. Experimental procedures and data collection

The experimental data utilized in this study was collected at the Ohio State University Biomechanics Laboratory. Trunk kinematics during experimental lifting tasks was recorded using the lumbar motion monitor (LMM). The LMM is essentially an exoskeleton of the spine in the form of a triaxial electro-goniometer that measures the instantaneous three-dimensional position, velocity, and acceleration. Table 1 shows all kinematic variables collected during the experimental trials and utilized in this study. For additional details about the design, accuracy, and application of the LMM, refer to Marras et al. (1992).

The EMG data was collected for 10 trunk muscles (see Fig. 2), including the right and left pairs of latissimus dorsi, erector spinae, rectus abdominus, external obliques, and internal obliques (see listing in Table 1). The locations of the electrodes were as follows: (1) latissimus dorsi muscles—at the most lateral portion of the muscle at the ninth thoracic vertebrae, (2) erector spinae muscles—over the largest muscle mass located by palpation and approximately 4 cm from the midline of the spine, (3) rectus abdominus muscle—3 cm from midline of the abdomen and 2 cm above the umbilicus, (4) external oblique muscles—10 cm from midline of the abdomen and 4 cm above the ilium at an angle of 45°, and (5) internal oblique muscles—4 cm above the ilium in the lumbar triangle at an angle of 45° (Mirka and Marras, 1993).

The EMG activity was collected from the five pairs of trunk muscles through the use of bipolar silver–silver chloride surface electrodes using standard EMG-recording

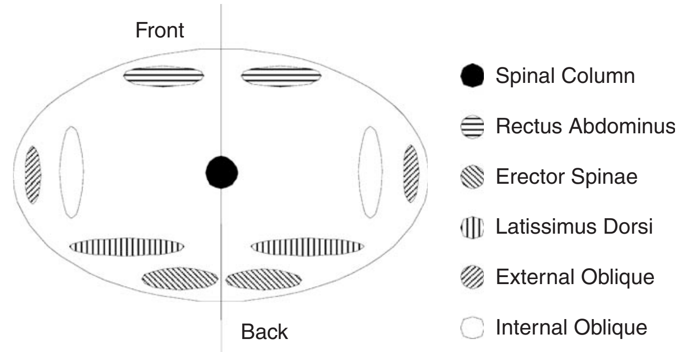

Fig. 2. Trunk muscles used for EMG data collection in the laboratory study (after Marras et al., 2002).

technique (National Institute for Occupational Safety and Health (NIOSH), 1991; Marras, 1990; Marras and Granata, 1995). The subjects were then placed in a rigid structure where maximum isometric exertions were performed. These standard maximum exertions were used for normalization of the EMG data (Marras and Mirka, 1993) include: extension at 20° of flexion, flexion in the upright posture, right and left lateral flexion in the upright posture, and right and left twisting in the upright posture.

The EMG signals were pre-amplified, high-passed filtered at 30 Hz, low-passed filtered at 1000 Hz, rectified, and integrated via a 20 ms sliding window hardware filter. Full-wave rectification of the raw data was done by applying the absolute value function to the raw data. Full-wave rectification folds the negative part of the raw signal above zero reference to join the positive half of the signal. Generally, full-wave rectification is desirable when the study objective is to examine the total amount of energy contained by the signal (Marras and Granata, 1995).

A force plate and set of electro-goniometers was used to accurately estimate the moments supported by the trunk during the lifts. The electro-goniometers assess the position of L_5/S_1 relative to the center of the force plate as well as measure the pelvic/hip orientation. The force and moments measured at the center of the force plate are then translated and rotated to L_5/S_1 by the method developed by Fathallah et al. (1997).

Table 1
Description of muscles and trunk-related model input variables

Acronym	
Muscle description	
RLD	Right lat. dorsi
LLD	Left lat. dorsi
RES	Right erector spinae
LES	Left erector spine
RRA	Right rectus abdominus
LRA	Left rectus abdominus
REO	Right external oblique
LEO	Left external oblique
RIO	Right internal oblique
LIO	Left internal oblique
Trunk-related variables	
SM	Sagittal moment
LM	Lateral moment
AM	Axial moment
PTAN	Pelvic tilt angle
PRAN	Pelvic rotation angle
STA	Sagittal trunk angle
LTAN	Lateral trunk angle
TTAN	Twist trunk angle

5.2. Experimental EMG data used in FRN model development

The data for FRRN model training and testing were randomly selected from the EMG data set of 20 male college students who served as subjects. (The EMG data for female subjects was also collected and the results are described elsewhere; see Karwowski et al., 2006). The utilized EMG data represented a total of 24 trials ($3 \times 2 \times 4$), with the combination of weight (15, 30, 50) lifted, asymmetry (0°, 60°), origin and destination of lift (floor-waist, floor-102 cm, knee-waist, knee-102 cm), and two replications of each trial, giving a total of 960 (time

Table 2
Experimental conditions for EMG data collection utilized in this study

Trial	Weight (LBS)	Asymmetry (deg)	Origin (CM)	Destination (CM)
1	15	60	Floor	Waist
2	15	60	Floor	102.00
3	15	60	Knee	Waist
4	15	60	Knee	102.00
5	15	0	Floor	Waist
6	15	0	Floor	102.00
7	15	0	Knee	Waist
8	15	0	Knee	102.00
9	30	60	Floor	Waist
10	30	60	Floor	102.00
11	30	60	Knee	Waist
12	30	60	Knee	102.00
13	30	0	Floor	Waist
14	30	0	Floor	102.00
15	30	0	Knee	Waist
16	30	0	Knee	102.00
17	50	60	Floor	Waist
18	50	60	Floor	102.00
19	50	60	Knee	Waist
20	50	60	Knee	102.00
21	50	0	Floor	Waist
22	50	0	Floor	102.00
23	50	0	Knee	Waist
24	50	0	Knee	102.00

domain) EMG samples ($24 \times 2 \times 20$ subjects). The experimental conditions for the study are shown in Table 2.

6. An EMG estimation model

In this study, the EMG estimation model was developed based on the methodologies of soft computing (Kosko, 1992; Karwowski et al., 1999). The applied fuzzy rule-based systems combine the universal approximation property with the ability to represent imprecise verbal knowledge expressed by decision rules. The hybridization of fuzzy systems and artificial NN has led to a new modeling paradigm, called fuzzy-NN (Ross, 1995; Wang and Mendel, 1992). This paradigm makes it possible to not only estimate a model from data but also capture the knowledge underlying the model behavior.

6.1. A FRRN

FRRN is a modification of a conventional fuzzy rule-based system which, in addition to modeling the input–output relationship, allows for modeling linear relationships between the input variables of the system (Gaweda et al., 2001, 2002). It has been shown that this approach produces accurate system models with reduced complexity. The FRRN can be represented schematically as a three-layer network structure (Gaweda and Zurada, 2003).

6.1.1. Layer 1—input membership functions

The linear relationship between two input variables is modeled by a two-dimensional Gaussian membership function of the form:

$$\mu(x_1, x_2; v_1, v_2, s_1, s_2, r) = \exp\left[-\left(\left(\frac{x_1 - v_1}{s_1\sqrt{1-r^2}}\right)^2 + \left(\frac{x_2 - v_2}{s_2\sqrt{1-r^2}}\right)^2 - 2r\frac{(x_1 - v_1)(x_2 - v_2)}{s_1 s_2 (1-r^2)}\right)\right], \quad (1)$$

where x_1 and x_2 are the input arguments, (v_1, v_2) are the center coordinates, (s_1, s_2) are the widths of the Gaussians projected on the axes of x_1 and x_2, respectively, and r is the strength of the linear relationship (correlation coefficient) between x_1 and x_2.

6.2. Layer 2—rule activations

The rule activation nodes receive the membership values from the Layer 1 nodes as inputs and produce the rule activation levels as outputs. The rule activation is determined by applying the product T-norm over the corresponding membership values.

6.3. Layer 3—defuzzification

The total FRRN output is computed as in the Takagi–Sugeno model (Takagi and Sugeno, 1985). In TS-model, the rule consequents are linear combinations of the input variables. Therefore, the accumulated model output is a weighted combination of local linear models (hyperplanes). For the purpose of knowedge extraction, these local models can be transformed into the position-gradient representation (Sugeno and Yasukawa, 1993).

Schematic representation of FRRN with three inputs and two rule nodes is shown in Fig. 3. In this figure, the symbols x_1 through x_3 represent a three-element input vector, A^i_{jk} represents a two-dimensional membership function (1) of the input variables j and k in rule i. The symbol b_{ij} represents a coefficient of a local linear model related to rule i and input variable j (Fig. 4).

6.4. EMG modeling approach

In this work, the FRRN was used to perform a mapping from the inputs space consisting of variables representing

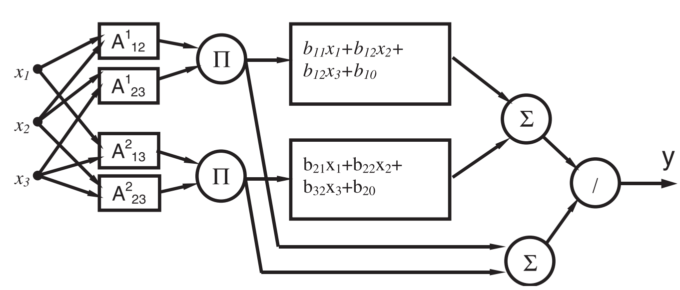

Fig. 3. Example of the simplified diagram of a 3-input variable fuzzy relational rule network (FRRN).

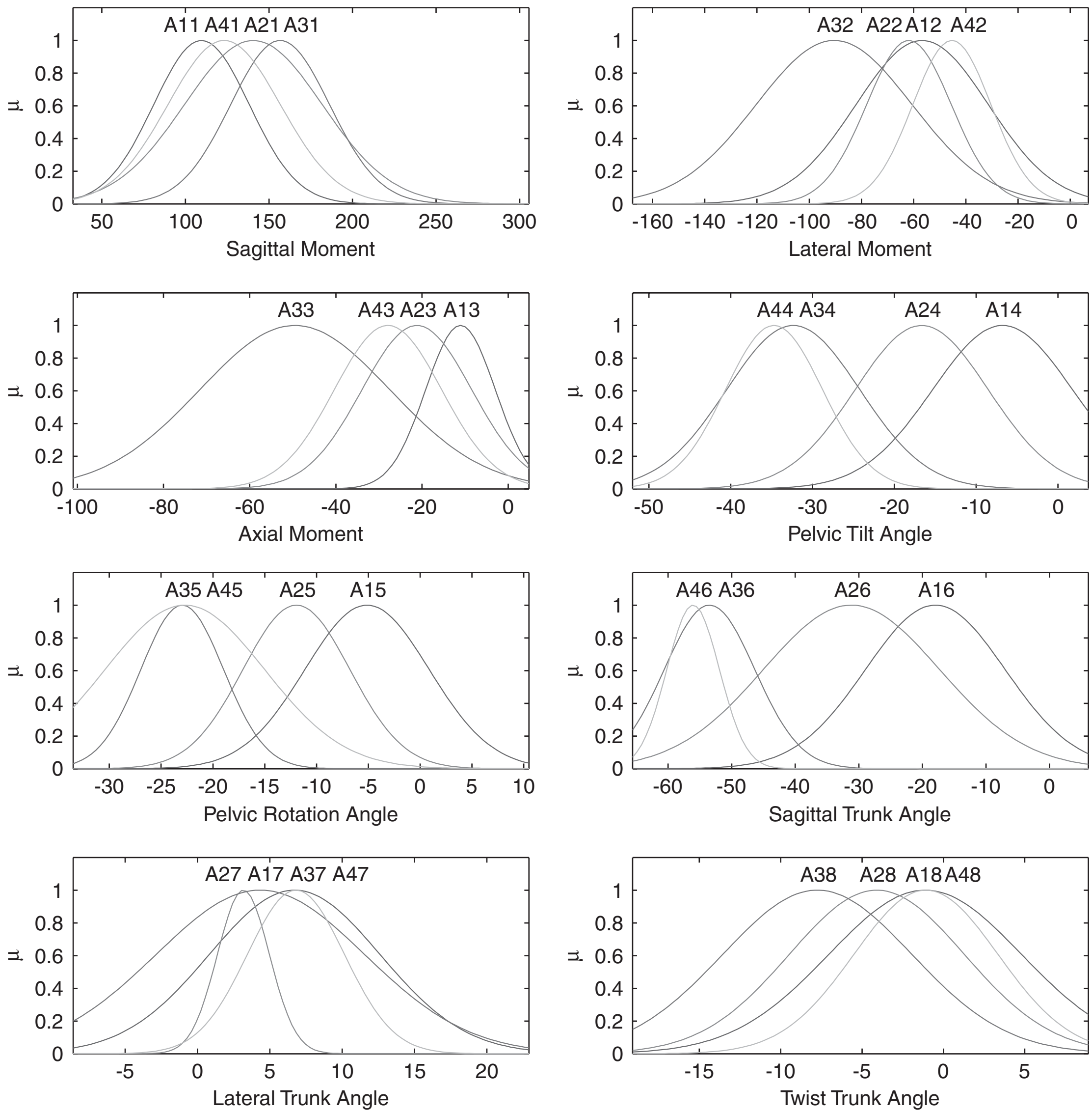

Fig. 4. Examples of FRRN generated one-dimensional membership functions for trunk-related variables.

trunk dynamics, i.e., sagittal, lateral, and axial moments, pelvic tilt and rotation angles, and sagittal, lateral, and axial trunk angles (see Table 1) into the output space of 10 EMG signals (entries 1 through 10 in Table 1). To accomplish this, multiple input single output (MISO) approach was adopted, allowing developing of 10 separate prediction models. A single model maps multiple trunk-related variables into one of the 10 EMG signals. The mapping performed by the model is static, i.e., the EMG signal at time instant t is estimated from the trunk-related variables measured at the same time instant t. For clarity of the presentation, we will omit the time index in the following presentation.

With numerical data available, the structure and the parameters of the FRRN model can be automatically identified using a data-driven method described in (Gaweda, 2002). More specifically, the structure generation determines the number of nodes in layer 2, i.e., the number of fuzzy rules and discovery of significant linear relationships between the input variables. The parameter estimation finds the values of v, s, and r in Eq. (1) and the coefficients b in Fig. 1. Further details of the method can be found in Gaweda and Zurada (2003).

7. Results

7.1. EMG estimation model (EMG-E)

The developed EMG estimation FRRN-based model utilized fuzzy rules with different pairs of trunk-related fuzzy variables as inputs. Table 3 provides examples of such rules for LES muscle for a single lifting trial. For each out of ten output variables (EMG values), linear correlation analysis was used to reveal the most significant trunk-related variables to be used as inputs. Fig. 6 presents examples of the fuzzy representation of input variables

Table 3
Example of fuzzy two-dimensional fuzzy rules for LES muscle

RULE1:

IF

A11 Sagittal Moment CORR (−0.92) A16 Sagittal Trunk Angle AND
A11 Sagittal Moment CORR (−0.62) A15 Pelvic Rotation Angle AND
A12 Lateral Moment CORR (0.99) A18 Twist Trunk Angle AND
A13 Axial Moment CORR (0.98) A14 Pelvic Tilt Angle AND
A14 Pelvic Tilt Angle CORR (0.95) A15 Pelvic Rotation Angle AND
A16 Sagittal Trunk Angle CORR (0.75) A17 Lateral Trunk Angle AND
A17 Lateral Trunk Angle CORR (0.57) A18 Twist Trunk Angle

THEN

Left Erector Spinae is 1.369157 AND
d (Left Erector Spinae)/d(Sagittal Moment) is 0.007530 AND
d (Left Erector Spinae)/d(Lateral Moment) is −0.003406 AND
d (Left Erector Spinae)/d(Axial Moment) is −0.001363 AND
d (Left Erector Spinae)/d(Pelvic Tilt Angle) is 0.033912 AND
d (Left Erector Spinae)/d(Pelvic Rotation Angle) is −0.021704 AND
d (Left Erector Spinae)/d(Sagittal Trunk Angle) is 0.028560 AND
d (Left Erector Spinae)/d(Lateral Trunk Angle) is 0.067151 AND
d (Left Erector Spinae)/d(Twist Trunk Angle) is −0.050245

RULE2:

IF

A21 Sagittal Moment CORR (−0.16) A25 Pelvic Rotation Angle AND
A21 Sagittal Moment CORR (−0.78) A22 Lateral Moment AND
A23 Axial Moment CORR (0.98) A24 Pelvic Tilt Angle AND
A24 Pelvic Tilt Angle CORR (0.92) A25 Pelvic Rotation Angle AND
A24 Pelvic Tilt Angle CORR (−0.26) A27 Lateral Trunk Angle AND
A25 Pelvic Rotation Angle CORR (−0.02) A26 Sagittal Trunk Angle AND
A26 Sagittal Trunk Angle CORR (0.87) A28 Twist Trunk Angle

THEN

Left Erector Spinae is 0.623423 AND
d (Left Erector Spinae)/d(Sagittal Moment) is 0.004495 AND
d (Left Erector Spinae)/d(Lateral Moment) is 0.001075 AND
d (Left Erector Spinae)/d(Axial Moment) is −0.004698 AND
d (Left Erector Spinae)/d(Pelvic Tilt Angle) is 0.020090 AND
d (Left Erector Spinae)/d(Pelvic Rotation Angle) is 0.005375 AND
d (Left Erector Spinae)/d(Sagittal Trunk Angle) is −0.002149 AND
d (Left Erector Spinae)/d(Lateral Trunk Angle) is 0.002746 AND
d (Left Erector Spinae)/d(Twist Trunk Angle) is 0.011573

Note: The acronym CORR(p) represents "correlated to degree p".

corresponding to the fuzzy rule R1 shown in Table 4. Fig. 5 shows examples of two-dimensional fuzzy membership functions for FRRN-generated fuzzy rules.

The EMG-E model was trained using data for 10 subjects and was tested using data from another ten subjects. A specific example of the outcome of model training with four fuzzy rules for RES muscle for a single trial #10 is shown in Table 4. Fig. 6 shows examples of model-generated membership functions corresponding to symbols A_1 through A_3 in the rules shown in Table 4. An example of the two-dimensional membership function representation of these rules is shown in Fig. 7.

For example, for a particular model that estimates EMG signal for RES muscle, the lateral trunk angle and pelvic rotation angle were found to be the most important trunk dynamics variables. The rules can be interpreted as follows. The symbols A_1 through A_4 represent the membership functions shown in Fig. 6a, b. Based on the shape and location of the membership function, a domain expert can assign a linguistic label to each symbol. For example, A_1 for lateral trunk angle could be interpreted and labeled as "large negative" (see Fig. 6a), while A_1 for *pelvic rotation angle* in Fig. 6b could be labeled as "close to zero". Using this interpretation, Rule 1 could read "If lateral trunk angle is large negative and pelvic rotation angle is close to zero then the current value of RES can be computed using the equation: 0.0034 Lateral Trunk Angle + 0.0248 Pelvic Rotation Angle + 0.2292".

The above implies that this equation has a strong influence on the model output as long as the actual value *lateral trunk angle* is large negative AND the actual value of *pelvic rotation angle* is close to zero. On the other hand, Rule 3 should be interpreted as follows. Labeling A_3 for *lateral trunk angle* as "small negative" (see Fig. 6a) and for *pelvic rotation angle* as "medium positive" (see Fig. 6b), Rule 3 reads "If small negative lateral trunk angle is strongly positively correlated with medium positive pelvic rotation angle then the current value of RES can be computed using equation: 0.0209 Lateral Trunk Angle−0.0060 Pelvic Rotation Angle + 0.8599".

The positive correlation between small negative *lateral trunk angle* and "medium positive" *pelvic rotation angle* can

Table 4
Examples of the FRRN-generated fuzzy rules for the RES muscle in trial 10

R_1:	
IF	Lateral Trunk Angle is A1 AND Pelvic Rotation Angle is A1
THEN	RES = 0.0034 Lateral Trunk Angle + 0.0248 Pelvic Rotation Angle + 0.2292
R_2:	
IF	Lateral Trunk Angle is A2 AND Pelvic Rotation Angle is A2
THEN	RES = 0.0146 Lateral Trunk Angle + 0.0034 Pelvic Rotation Angle + 0.2845
R_3:	
IF	A3 Lateral Trunk Angle CORR (0.69) A3 Pelvic Rotation Angle
THEN	RES = 0.0209 Lateral Trunk Angle—0.0060 Pelvic Rotation Angle + 0.8599
R_4:	
IF	A4 Lateral Trunk Angle CORR (0.91) A4 Pelvic Rotation Angle
THEN	RES = 0.0265 Lateral Trunk Angle—0.0073 Pelvic Rotation Angle + 1.3979

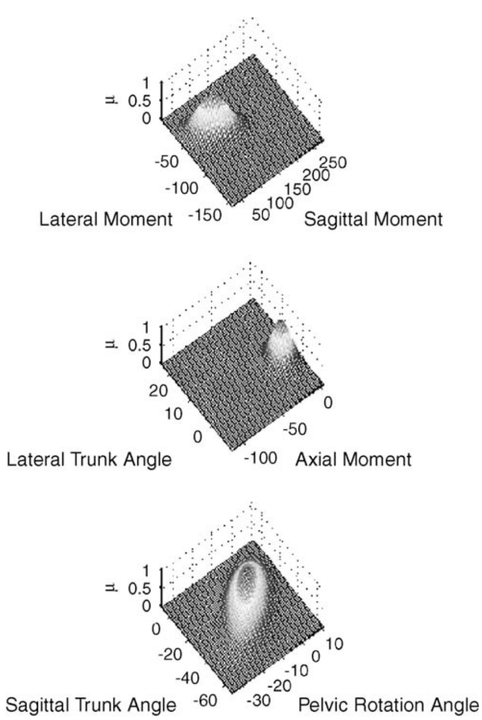

Fig. 5. Graphical representation of two-dimensional membership functions for FRRN-generated fuzzy rules.

be interpreted as follows. The centers of the membership functions A3 are −15 for the *lateral trunk angle* and 22 for the *pelvic rotation angle*. Rule 3 states that the

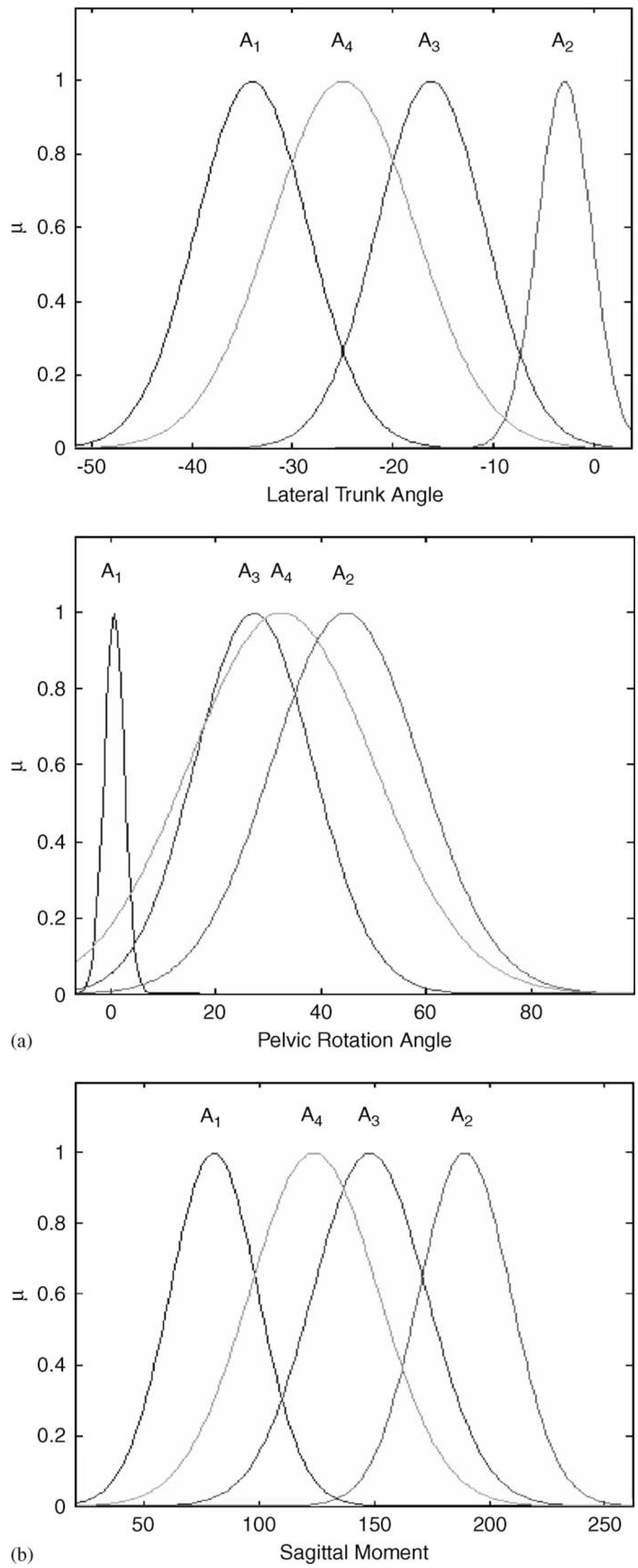

Fig. 6. (a) Examples of unidimensional fuzzy membership functions for RES model in Trial 10. (b) Examples of unidimensional fuzzy membership functions for LLD model in Trial 24. Representation of two-dimensional membership functions for FRRN-generated fuzzy rules.

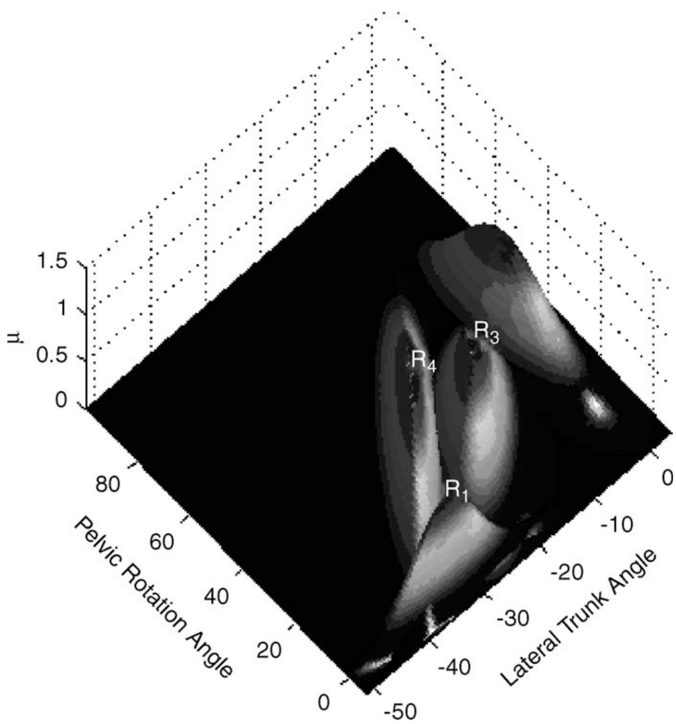

Fig. 7. Example of two-dimensional FRRN rules for RES model for a single-lifting trial.

corresponding RES equation has a strong influence on the model output as long as the actual value of lateral trunk angle is small negative and less than −15 while the actual value of pelvic rotation angle is medium positive and less than 22. The equation has also a strong influence on the model output when the actual value of lateral trunk angle is small negative and greater than −15 while the actual value of pelvic rotation angle is medium positive and greater than 22. It should be pointed out that the input variables in Rules 1 and 2 do not exhibit linear relationship. This can be better observed in the two-dimensional membership functions (see Fig. 7), which are three-dimensional plots of Eq. (1).

7.2. *EMG estimation model validation*

The developed model was validated by comparing the estimated EMG values with the EMG data for the 10 test subjects (a total of 480 EMG signals for each of the ten muscles tested) that were not used in model development. Examples of the predicted EMG signals are shown in Fig. 8. The value of the MAE indicates the error between the actual (EMG_{ACT}) values and model estimates (EMG_{EST}):

$$MAE = \sum_t (EMG_{ACT}(t) - EMG_{EST}(t))/N_t,$$

where symbol t denotes index of data vector at time t and N_t is the number of data samples.

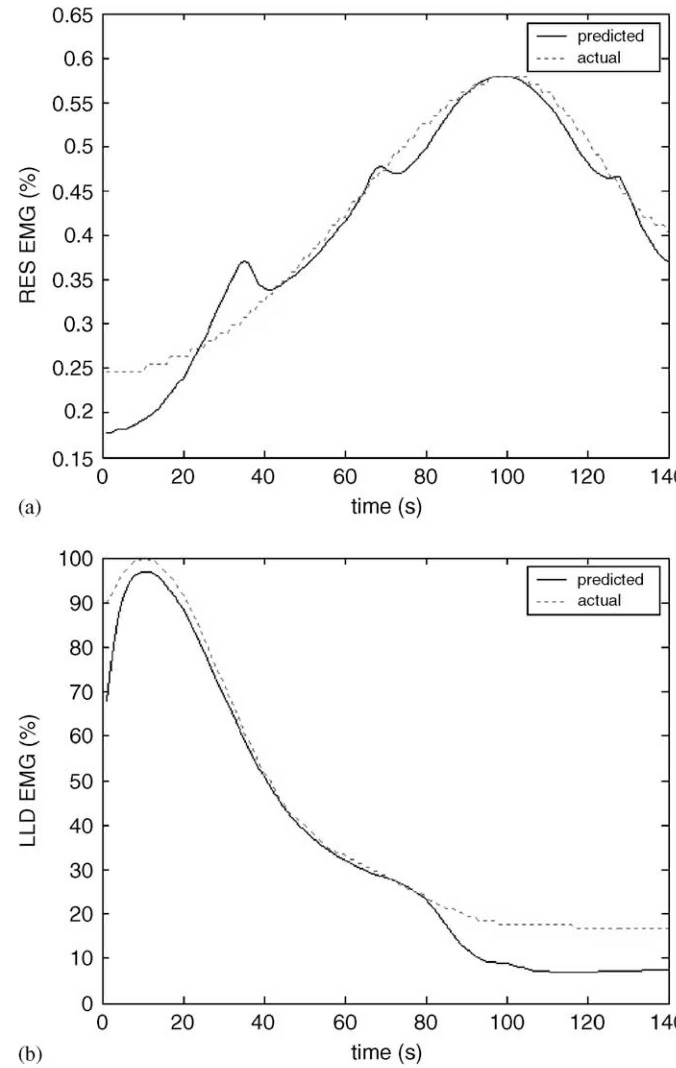

Fig. 8. (a) Demonstration of EMG estimation for a given subject under single lifting trial (RES muscle). (b) Demonstration of EMG estimation for a given subject under single lifting trials (LLD muscle).

Overall, across all 10-trunk muscles, the average value of MAE was 6.03% (SD = 1.36%) for training data (see Table 5) and 9.9% (SD = 1.44%) for testing data (see Table 6). The largest MAE value for testing data occurred for the right external oblique (REO) muscle RRA under conditions of asymmetrical lifting task, with 60° of trunk twisting. Fig. 9 illustrates the overall quality of the developed EMG estimation system for all investigated muscles.

8. Conclusions

As discussed by Marras (2005), the knowledge of how the trunk muscles are recruited during a particular work task is the key to understanding the magnitude of spine loading and risk of low back disorders due to the lifting tasks. Thus, it is important to develop a system that is capable of realistically predicting multiple trunk muscle activities in response to a variety of workplace dimensions

Table 5
Mean absolute error (%) for FRRN model training EMG data

Trial	RLD	LLD	RES	LES	RRA	LRA	REO	LEO	LIO	RIO
1	4.3	7.2	6.8	5.7	4.3	4.9	2.8	3.4	4.9	5.0
2	3.5	6.2	3.9	5.6	3.0	9.7	6.2	9.8	5.6	9.5
3	5.8	7.2	7.7	7.2	3.8	7.5	3.0	3.6	4.4	5.0
4	3.4	3.4	4.0	7.6	3.9	5.9	4.4	7.6	5.0	6.1
5	4.2	8.9	4.7	5.3	3.1	4.3	6.9	6.4	5.4	8.3
6	5.5	6.5	6.3	5.6	11.2	7.9	7.1	9.8	7.1	12.0
7	7.4	7.1	5.3	4.4	4.8	4.1	4.9	5.3	4.5	5.5
8	5.8	8.9	6.2	5.8	6.0	6.9	10.4	10.6	12.0	11.7
9	12.1	9.5	8.8	11.4	11.0	11.4	12.6	14.9	10.5	11.1
10	13.0	13.0	12.5	10.9	11.3	13.9	11.4	11.8	12.7	11.6
11	12.3	11.5	13.1	13.0	12.1	10.1	10.9	11.5	13.4	10.7
12	11.5	11.3	10.3	12.6	8.1	10.4	11.0	9.6	9.5	11.5
13	8.0	9.1	10.5	12.0	8.4	11.0	9.8	10.3	9.4	10.7
14	9.3	9.7	7.9	7.5	10.5	11.4	9.5	9.5	12.7	11.1
15	11.9	9.5	8.2	10.1	13.0	8.8	9.9	10.3	8.6	12.3
16	10.6	8.6	1.8	1.2	1.4	1.8	1.5	1.6	1.2	1.7
17	1.7	2.0	1.8	2.2	1.9	1.8	1.6	2.0	2.3	2.8
18	2.3	2.7	2.2	1.8	1.6	2.8	1.6	1.4	1.7	1.1
19	1.2	1.8	1.3	1.7	2.8	2.0	1.9	1.3	1.8	1.8
20	1.8	1.3	1.2	1.3	1.6	1.4	0.9	1.4	1.4	2.4
21	1.6	1.7	1.8	1.5	1.6	1.3	2.7	2.7	2.4	2.2
22	2.2	1.7	1.7	2.5	1.4	1.1	1.2	1.2	1.2	1.2
23	1.4	2.0	2.5	2.5	1.4	1.3	1.8	1.2	2.1	2.7
24	2.3	2.4	1.3	1.7	1.1	1.5	2.6	2.6	2.6	4.9
25	1.9	1.9	1.7	2.6	4.4	5.0	4.1	3.9	3.3	2.9
26	2.7	2.5	3.6	2.7	2.2	1.9	1.2	1.2	1.6	2.0
27	4.9	3.1	2.2	1.7	1.7	2.4	2.4	2.0	2.6	2.3
28	2.3	2.4	1.2	2.6	3.5	3.1	3.2	4.2	3.2	2.3
29	3.4	1.8	3.6	4.5	4.0	3.6	3.2	4.6	2.3	2.7
30	2.8	2.2	1.9	2.2	1.8	2.8	1.7	2.4	3.7	3.5
31	2.9	2.6	2.8	3.6	9.5	8.1	10.0	7.9	6.5	8.1
32	7.3	9.1	11.3	11.2	9.7	8.7	11.2	11.7	8.6	12.8
33	12.2	15.6	10.8	11.3	10.4	12.7	10.8	9.3	10.2	11.7
34	8.8	9.6	12.2	9.2	8.2	8.3	11.5	10.8	9.8	11.7
35	10.7	8.7	10.8	9.3	10.4	11.6	7.0	8.4	5.8	8.1
36	7.0	5.3	5.7	10.3	7.9	6.6	6.2	6.8	6.6	6.3
37	8.7	6.9	5.2	6.3	6.7	6.3	9.8	10.3	6.5	8.3
38	9.9	10.4	8.9	8.0	7.4	7.9	6.6	8.9	7.4	6.6

Table 6
Mean absolute error (%) for FRRN model testing EMG data

Trial	RLD	LLD	RES	LES	RRA	LRA	REO	LEO	LIO	RIO
1	6.8	7.1	5.0	9.0	4.9	6.9	7.1	7.5	6.6	11.2
2	8.1	8.9	10.6	13.5	9.2	17.3	15.9	14.5	8.0	15.5
3	17.4	11.6	15.1	18.7	5.0	8.3	7.5	7.0	6.0	9.8
4	7.2	8.9	11.0	11.3	6.3	11.0	11.2	14.6	8.3	7.6
5	6.1	8.9	8.1	10.2	5.8	5.3	13.5	12.5	8.0	8.7
6	10.4	7.5	6.3	7.1	27.5	11.1	13.9	18.2	14.3	14.6
7	10.2	17.9	5.4	5.7	6.3	5.8	7.5	8.0	7.7	6.6
8	12.2	11.6	8.4	11.9	7.5	10.2	11.9	15.9	15.8	14.1
9	15.5	17.2	21.1	21.0	14.4	11.7	14.8	15.0	11.1	15.5
10	14.9	14.8	13.5	12.4	11.1	12.9	20.7	14.2	14.8	12.0
11	13.1	15.5	13.3	16.5	15.1	14.8	12.9	16.3	11.8	15.6
12	11.0	14.4	13.4	17.0	14.8	10.5	13.2	18.6	13.6	15.5
13	23.8	18.9	14.5	15.5	16.0	15.3	16.2	14.7	17.9	14.2
14	13.6	13.9	13.5	12.6	19.3	14.6	14.7	12.0	17.1	13.0
15	16.2	18.3	13.8	13.1	14.7	15.8	12.8	13.8	14.9	17.2
16	17.0	13.4	4.0	3.4	3.5	3.9	3.9	3.9	3.4	3.5

Table 6 (*continued*)

Trial	RLD	LLD	RES	LES	RRA	LRA	REO	LEO	LIO	RIO
17	4.4	5.0	3.8	5.4	4.7	4.3	3.6	3.9	4.6	5.3
18	4.6	5.3	5.3	4.8	4.1	5.8	3.8	4.2	3.9	3.3
19	5.2	3.1	3.5	4.0	4.4	4.3	4.2	4.2	5.0	4.8
20	4.5	3.0	3.0	3.1	3.5	4.2	3.3	3.0	4.8	5.3
21	3.0	3.5	3.7	4.0	3.4	3.9	5.0	5.0	3.5	4.4
22	4.8	5.1	3.8	4.1	4.3	3.5	3.0	3.1	3.6	3.7
23	2.5	3.2	4.7	4.1	3.2	4.0	4.3	5.0	6.6	4.9
24	4.5	3.7	3.5	4.3	3.5	3.3	5.2	6.2	4.1	4.0
25	3.5	3.1	3.9	6.7	8.1	7.1	3.7	5.4	5.8	6.3
26	4.0	4.3	5.5	4.5	3.5	4.2	3.4	3.6	4.3	4.0
27	5.6	5.8	4.1	4.5	5.3	4.7	6.3	5.8	5.4	3.6
28	3.6	4.0	7.5	3.0	7.1	8.7	3.3	5.2	4.0	4.2
29	3.5	3.7	9.0	11.3	5.7	6.3	6.1	6.9	5.5	5.5
30	6.0	5.6	5.0	3.7	3.2	5.0	4.5	3.2	7.5	7.6
31	5.0	4.7	5.3	4.0	15.1	12.9	9.5	13.3	15.8	14.8
32	14.0	13.8	12.1	18.5	10.4	17.6	27.0	15.4	11.0	12.7
33	11.6	18.5	15.1	19.1	19.4	22.8	19.0	17.7	14.8	21.2
34	15.1	10.1	12.8	12.5	14.7	13.7	19.4	18.0	10.0	12.5
35	12.2	19.8	18.7	18.4	18.7	16.7	14.3	14.9	20.7	22.3
36	14.5	13.3	15.5	15.8	15.4	13.3	15.9	15.0	13.1	11.9
37	18.9	12.8	14.9	9.8	14.4	17.3	14.8	16.1	14.3	14.4
38	16.2	14.5	16.7	20.3	15.8	12.6	12.9	15.7	14.4	17.2

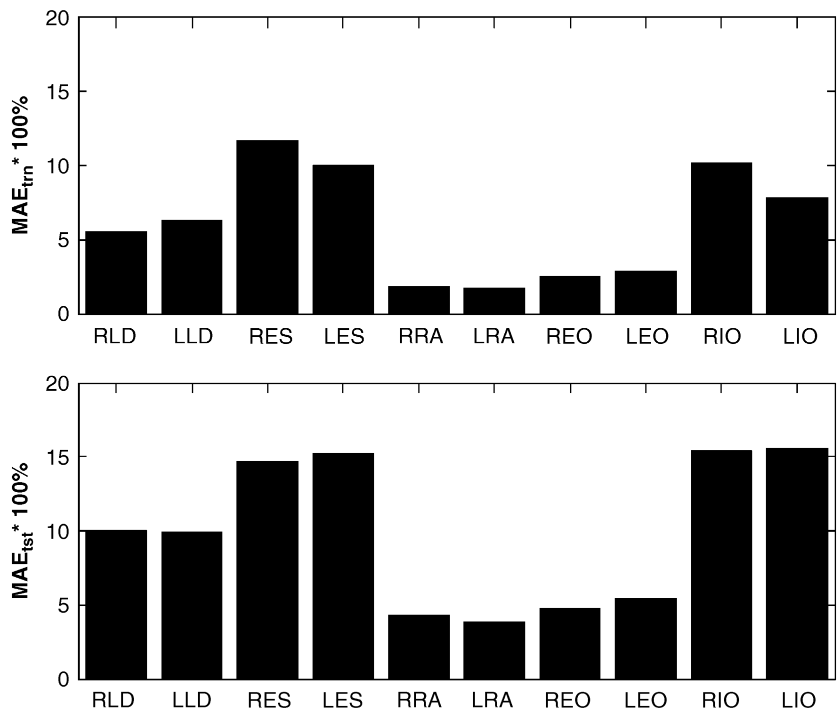

Fig. 9. Average mean absolute errors for training (top) and testing (bottom) EMG estimation results.

(physical, psychosocial, and individual). In our earlier study (Lee et al., 2003) we have developed a neuro-fuzzy model for estimating only the normalized peak EMG values for 10-trunk muscles based on two task variables, i.e. trunk moment and trunk velocity as inputs. We have postulated that concluded that estimation of the peak EMG responses in manual lifting tasks was feasible, and that model performance could be improved by increasing the number of system input variables.

The present study focused, for the first time, on estimating the time domain EMG responses of human trunk muscles due to manual lifting based on different set of input variables, namely trunk angels and moments and pelvic tilt and rotation angles. The results showed that application of the *Fuzzy Relational Rule Network* provides for a reasonable level of accuracy in estimating time domain EMG responses for a limited lifting task conditions. Given the recent advances in soft computing methodology, including neuro-fuzzy modeling techniques, one can reasonably expect that developed model can be extended to different lifting task conditions. Furthermore, model performance with respect to quality of the EMG estimations can still be improved by incorporating additional trunk kinematics variables, such as sagittal, lateral and axial trunk velocities and accelerations, as well as individual characteristics of the subjects (age, height, weight, etc.) as inputs to the model.

Future efforts will focus on utilizing the spine motion dynamics to simultaneously estimate EMG activity for trunk muscles with due consideration of the related muscle coactivity under a greater number of lifting task conditions. Future efforts will also aim at developing a soft computing-based spine-loading estimating system capable of accounting for musculoskeletal responses to variety of physical loads under a broad range of manual lifting tasks (Hou et al., 2005, 2006). This will require development of the hybrid neuro-fuzzy system based upon extensive databases that are capable of accounting for relevant workplace-related factors, and consideration of psychosocial factors, and individual characteristics of the worker.

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