NEURO-FUZZY MODELING OF MANUAL MATERIALS HANDLING

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ÖZET

Bu çalışmada, bel ve sırt ağrılarının en önemli nedenlerinden biri olarak belirtilen elle yük kaldırma işlerinin modellenmesi için dilsel bir yaklaşım sunulmuş olup, duruma özel çözümlerin ortadan kaldırılması, ağır hesaplamalar içeren ve pahalı deneysel yüklere sahip çözümlerin azaltılması amaçlanmıştır. Kaldırma eyleminin biyodinamiğini etkileyen bir takım parametrelerden; kaldırma süresi, kaldırılan yük, bireyin boyu ve kütlesinin bulanık olduğu düşünülerek bir adaptif sinirsel bulanık çıkarım sistemi (ANFIS) eğitilip, kaldırma esnasında kalça eklemine etkiyen maksimum kuvvet ve momentlerin tahmini yapılmıştır. Deneysel ve teorik hesaplamalardan elde edilen birbirinden farklı iki örneklem seti, biyomekanik ve deneysel modelin yerini alabilecek olan sinir ağının eğitiminde kullanılmıştır. Sonuçlar, deneysel ve hesaplamalı dahil olmak üzere eğitim için kullanılan orjinal veriler ile karşılaştırılmış ve iyi bir uyumun yakalandığı gözlenmiştir.

Anahtar Kelimeler: Bulanık Mantık, Yapay Sinir Ağları, ANFIS, Elle Yük Kaldırma, Bel Ağrısı

ELLE YÜK KALDIRMANIN BULANIK SİNİR AĞLARI İLE MODELLENMESİ

ABSTRACT

This paper presents a linguistic approach for the modeling of manual materials handling tasks that are being reported to be one of the most important causes to lower back pains, with an aim of eliminating subject specific solutions, and reducing computationally and experimentally hefty and expensive solutions. Considering that some of the parameters affecting the biodynamics of the lift are fuzzy, such as the duration of the lift, the height and mass of the subject, and the load lifted, an adaptive neuro-fuzzy inference system (ANFIS) was trained to estimate maximum forces and moments being generated at the hip joint during lifting tasks. Two different sampling sets obtained separately from experiments and theoretical computations were used to train and test the neural net that would be used in place of experimental or biomechanical model. The results were compared with the original data sets used for training, including experimental and computational, and a good correspondence were observed.

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1. INTRODUCTION

Manual materials handling (MMH) is very frequent in industry in spite of an extensive advancement in lifting and carrying technologies[1]. Considering that the manual materials handling tasks are one of the most important causes of low back disorders [2] and that they are one of the major lost sources of work and capital[3], they need more attention to be considered[4]. Therefore, the causes and mechanisms of LBP must be well understood to be able to design lifting tasks and prevent injuries caused by them. For this purpose modeling and analysis of MMH has been attempted via various ways[5], for instance, biomechanical analysis of human body engaging MMH has been one of the major approaches to estimate the resulting forces and moments at the back [6].Static [7, 8]and dynamic models in 2-D [9]or in 3-D [10]for symmetric [2]and asymmetric[11] lifting tasks can be referred to name some. In the solution of biomechanics problems, optimization has been extensively utilized mainly because of their highly redundant nature and their compliance with some optimality criteria[12, 13, 14].

Besides biomechanical models in MMH studies, physiological, epidemiological, and psychophysical models are available in the literature. Energy expenditure, heart rate, and electromyogram measurements are the main aspects of the physiological studies. Epidemiological studies relate injuries to components of workload, while psychophysical studies consider the perceived workload[15, 16, 5]. In some research, postural analyses are used to develop ergonomic interventions, where either observational or instrumental techniques are basically utilized. Although pen-and-paper based observational techniques are inexpensive, they are reported to be subjective and imprecise, while instrument based observations are expensive but relatively accurate [5, 17, 18].

Considering that the dynamic models of biomechanical systems often possess high dimensions, severe nonlinearity, complex coupling, high redundancy, and various constraints [19, 20, 21], soft computing techniques such as artificial neural networks and fuzzy logic has become one of the emerging fields among the biomechanics researchers. For instance, [22] pioneered a linguistic fuzzy logic approach to model the stress associated with the manual lifting, and it had been widely quoted and applied in theoretical, laboratory and work field situations [15, 23].[24] predicted dynamic forces on the lumbar joint using an artificial neural network, based on kinematic variables directly, instead of using a costly way of measuring electromyography signals and a biomechanics model. In another work by the same research group [25], dynamic spinal forces were estimated by using a fuzzy neural network, where the advantages of both fuzzy and neural nets were combined. [26] simulated human lifting motions using fuzzy logic control for a 2-D five-segment human body model to predict lifting motion trajectories.

In this study, however, a different approach was developed for the biomechanics analysis of lifting with a special attention given to the parameters affecting the dynamics of the task by treating them as fuzzy parameters. Since the parameters, such as the duration of the lift, the height and mass of the subject, and the load lifted, are all fuzzy, a model taking the level of fuzziness into account serves as a training and estimation tool for manual materials handling task. For the reasons set forth, a Sugeno type neuro-fuzzy model (ANFIS) was established for the estimation of the maximum forces and moments developed at the hip joint during the lifting motion. The data for training the net were obtained both experimentally and theoretically. The forces and moments obtained from the ANFIS model were compared with the computed results from experiments and the optimization-based biomechanics model, and a very good correspondence was observed. Based on this confidence it was concluded that,once the net is trained, it can be used for designing broader cases of lifting tasks rather than using subject specific experimental and/or biomechanical models.

2. MATERIALS AND METHOD

Linguistic expressions, such as fast or slow,can be adapted into biomechanical models by using fuzzy logic through some fuzzy sets and rules[22, 26]. As a first step of the application, the duration of the lift, the height and mass of the subject, and the load lifted were considered to be the fuzzy expressions related to biomechanics of lifting, and fuzzified into tree levels as shown on Table 1.

Table 1. Fuzzy parameter levels related to MMH

Input	Set 1 (Least)	Set 2 (Moderate)	Set 3 (Greatest)
Object Mass	Thin (N)	Fit (I)	Fat (A)
Object Height	Short (S)	Medium (M)	Tall (T)
Lift Duration	Slow (W)	Modest (D)	Fast (F)
Load Lifted	Light (L)	Moderate (R)	Heavy (H)

A schematic representation of these fuzzy inputs was also depicted in Fig. 1 at their three levels of application, namely the least, moderate, and greatest.

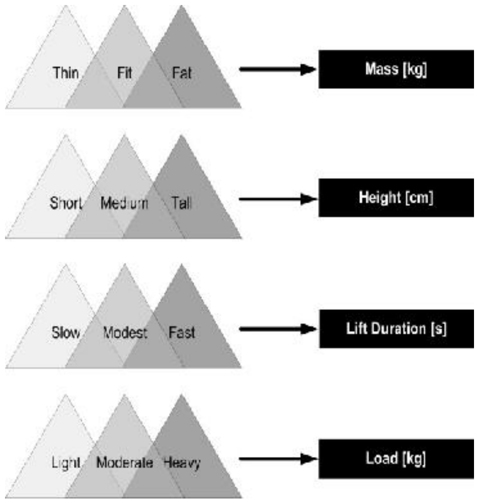

Fig. 1. Schematic representation of fuzzy inputs

Data were generated, as a second step, both theoretically and experimentally in accordance with the fuzzy levels described above (Fig. 1). Theoretical data were produced based on the computer program previously developed for simulations of a lifting model constructed with five segments in 2-D[27]. The differential equations of motion were obtained from Newton-Euler formulation, and the joint moments with joint dynamic strengths were used to construct the objective function. Then a genetic algorithm program developed for solving inverse dynamics problem to estimate maximum forces and moments generated at the hip joint during the lifts.
Mass and height of subject and mass of the load lifted directly appeared as parameters in the equations of motion while the duration of the lift was taken as the simulation time for the computations. On the other hand, the horizontal and vertical distances of the load were the initial conditions to the differential equations of motion, from which the initial orientation of the link were obtained. The problem was solved for a single lift assuming a sagittally symmetric 2D motion, hence, both hands moving in unison as if subjects holding handle of the test device. Furthermore, interference of load into subject's body was avoided by building constraints into the optimization program.
[A] From the biomechanical perspective, the force and moment at the lower back or hip should at least be affected by the weight of the object, horizontal distance (size of the object), the vertical travel distance (from origin to destination of lift), the origin of lift (the beginning of the lift), duration and frequency of lift.
The experimental data, on the other hand, were provided by a research group at Ohio State University[28], which is participated by ten male and ten female subjects with the anthropometric data shown on Table 2. The experiments repeated for three (two for females) simulated loads with three movement times. The masses lifted were 6.8, 13.6, and 20.5 kilograms. Female subjects did not perform the 20.5 kg lifts. The lifting times were approximately 1, 2, and 3 seconds.

Table 2. Anthropometric data of subjects and their standard deviations (s.d.)

Gender	Age (year)	Mass (kg)	Height (cm)
Male	26,1 (3,8)	85,3 (13,9)	178,6 (10,7)
Female	24,2 (2,4)	57,2 (4,7)	165,0 (2,6)
Population	25,2 (3,3)	71,3 (17,6)	171,8 (10,3)

The raw data included relative angular measurements between the subjects' body segments during a sagittally symmetric manual lift. The data were then numerically processed through the same set of dynamic model to compute the maximum forces and moments at the hip joint without a need for optimization.

In the last stage of the study, the estimated data from optimizations and the computed data from experiments were separately used to train two artificial neural networks for the maximum force and moment estimations. For the trainings, the genfis2 algorithm available in MATLAB Fuzzy Logic Toolbox was utilized, which generated a single-output Sugeno-type fuzzy inference system.

Artificial neural networks (ANN) are mostly used to construct a model for a physical system or a process by imitating human brain. ANN are first trained with the samples related to the problem under investigation, then expected to result in some conclusions about a new data set provided to them. Being inspired by biological neural cells, an artificial neuron is designed by using the terms like input, weights, summation, activation function, and output. Similarly, ANN are constructed in layers called input layer, intermediate layers, and output layer by collecting numerous artificial neural cells together [29].

On the other hand, fuzzy logic and neural networks are used together in an adaptive neuro-fuzzy inference system (ANFIS) to combine the advantages of both methods [30]. Sugeno type fuzzy inference system was used in the construction of ANFIS model by using five layers, namely fuzzification layer, signal multiplication layer, normalization layer, fuzzy inference layer, and defuzzification layer.

The constructed ANFIS model has four inputs and two outputs. Height and mass of subjects, lifting times, and loads lifted are the inputs while the maximum forces and moments at the hip joint are the outputs. The model was trained and run for maximum forces and moments separately since the program being used allowed only one output at a time.

3. RESULTS AND DISCUSSION

For the training of nets 21 different combinations were used, such as a thin-tall subject lifting a heavy weight slowly (NTWH), in such a way to cover almost all possibilities. Once the net was trained, five new set of data were generated for testing the performance of the net, which were not among the training data.

Table 3 includes the testing data and their ANFIS estimates for the maximum forces (N) formed during a lift for both theoretical and experimental data. Absolute errors were also tabulated on the table to investigate how close the estimates to the test data. In the theoretical part, genetic algorithm (GA) was used to get maximum forces at the hip joint during a specified lift, such as “a fat and medium height subject lifting a light load with a modest speed (AMDL)”. The same data was also pictorially presented on Fig. 2 as a bar graph.

Table 3. Test data and their ANFIS estimates for maximum forces (N)

Linguistic Variable	Theoretical			Experimental		
	GA	ANFIS	% error	Exp Based	ANFIS	% error
AMDL	761	918	20.63	769	804	4.55
AMFH	1096	1193	8.85	1071	1110	3.64
NMDH	855	916	7.13	841	846	0.59
NMFR	859	886	3.14	832	854	2.64
NMWL	762	704	7.61	832	660	20.67

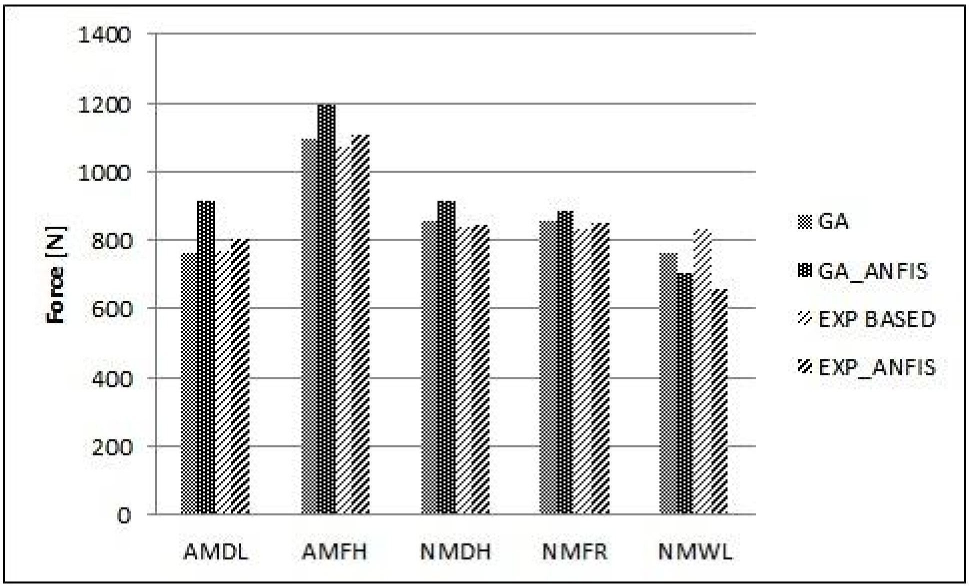

Fig. 2. Test data and their ANFIS estimates for maximum forces (N)

In a similar fashion, Table 4 includes the testing data and their ANFIS estimates for the maximum moments (N.m) formed during a lift for both theoretical and experimental data. In the theoretical part, as mentioned earlier, genetic algorithm (GA) was used to get maximum moments at the hip joint during a specified lift for again the same type of the lift. Again the experimental data and the theoretically produced data were pictorially shown on Fig. 3 as a bar graph together with their estimated counterparts.

Table 4. Test data and their ANFIS estimatesfor maximum moments (N.m)

Linguistic Variable	Theoretical			Experimental		
	GA	ANFIS	% error	Exp Based	ANFIS	% error
AMDL	223	265	18.83	227	233	2.64
AMFH	329	407	23.70	349	397	13.75
NMDH	304	305	0.32	309	280	9.38
NMFR	314	303	3.50	307	325	5.86
NMWL	246	203	17.47	243	218	10.28

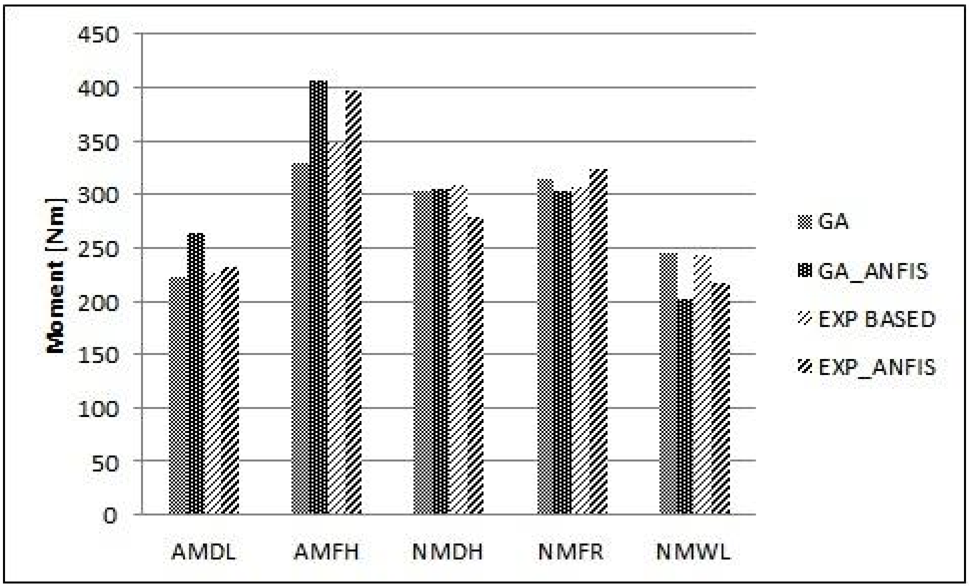

Fig. 3. Test data and their ANFIS estimates for maximum moments (N.m)

Data sets including theoretical and experimental results for maximum forces and moments generated during a lifting task on the hip joint were compared with their model output, and a fairly good correspondence was observed. Although the estimated results were close to the data used for training the neural nets, and performance were high, the estimated results for testing data were mostly higher, which can be desirable in that higher results serve like a safety factor in a MMH task design, because such a consideration is directly related to the human health in a positive manner. The results poorly imitating the real situation can be refined by using a larger number of data points in the training stage.

4. CONCLUSION

Development of a fuzzy logic based linguistic model for manual materials handling tasks was the focus of the present study. Therefore, a methodology was developed to eliminate subject-specific solutions, computationally expensive biomechanical models, and experimentally difficult and expensive work by training a neural net to be used with fuzzy inputs to estimate the injury possibilities during manual lifts.
The maximum forces and moments that are thought of responsible from the low back injuries could be estimated by the trained neural net with some linguistic inputs such as ‘heavy weight’, ‘fast lifting’, etc. This type of programming enables the industrial organizer to design proper lifting task for workers without a need for any biomechanics model or experimental work. Considering that there is no practical use of ‘too’ sensitive computations of forces and moments formed at the hip joint during a lift, this program gives a rough idea if a lifting task is whether suitable to a worker or not by just inputting his/her physical properties to the program.
The approach can be improved, though, by training neural net with a larger group of data to represent diversity of the real lifting cases. Although there were 34 = 81 possibilities for the input combinations to the neural net, 21 sets of data were used in the training because of the shortage of experimental data. By increasing the training data to cover a broader range of lifting tasks, it is surely possible to get a finer result.
Another improvement can be made in the presentation of network output, namely, instead of giving just numbers for maximum forces and moments, it would be much beneficial to give linguistic expressions like “it is safe to lift”, “it is dangerous to lift” or “it is most likely injurious to lift”, etc. to give a meaningful output to the end user.

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