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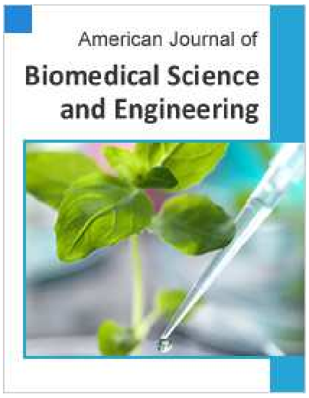

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Prediction of Low Back Pain Using a Fuzzy Logic Algorithm

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Abstract
Microinjury and inflammation on the connective tissues in low back pain (LBP) patients may be led by a chronic, local increase in stress. This study aims at discovering if the intensity level of the LBP can be identified objectively. 59 healthy voluntary subjects as a control group, and 110 patients as LBP group, in total 169 subjects, participated to the study. The skin resistance and visual analog scale (VAS) values have been measured for all the subjects. These values have been accepted as the input variables for the developed fuzzy logic algorithm. The fuzzy logic algorithm identifying the healthy and LBP subjects evaluated the level of the LBP was found to be an advantageous approach in addition to existing unbiased approaches. The intensity level of the LBP evaluated subjectively can be assessed objectively using the current fuzzy logic algorithm. Since the fuzzy logic approach is non-invasive, there is no requirement for any surgical operation to diagnose the patients. Thus instead of the VAS method which is a subjective method, the presented objective method may be used for the scaling the intensity level of the pain.

1. Introduction

Low back pain (LBP) creating dysfunction in muscular-skeletal system is one of the most common subacute/chronic pain syndromes. Forcing of muscles, connective and soft tissues, deformation of vertebrae, disc lesion or the inflammatory mediators associated with disc’s nucleus pulposus cause pain [7]. There are many ways to diagnose type, duration, location and intensity of a patient’s LBP. One of them is to diagnose in terms of the patient’s own statement. This approach is known to be visual analog scale (VAS). The patient's pain can be measured using the VAS scale, as follows. A line numbered from 0 (no pain) to 10 (maximum pain) is shown to the patients. The patients are directed to indicate the level of pain on this scale. Thus, the pain is determined subjectively [5]. Although the VAS was reported to be reliable and to be a valuable method in the literature, the determination of the effect level of pain remains inadequate [14]. Skin resistance has been used since 1930s to determine sites of pathological conditions and is defined as the resistance offered to the passage of an electrical current (direct current) through the skin [9, 10]. Skin resistance is related to skin conductance, which changes in the presence of sweat, a fluid composed of water and ions.

Fuzzy logic is a computational paradigm that provides a mathematical tool for representing and manipulating information in a way that resembles human communication and reasoning processes [17]. Fuzzy logic has been used in the biological and agricultural systems [4]. Depth of anesthesia can be predicted using fuzzy logic [1, 8, 18]. Data from different tools/methods such as ultrasonography, GCS and EEG can be used to develop models using fuzzy logic [2, 6, 19].

There are also various studies in recent years to diagnose the LBP based on skin conductivity as a replacement method for the VAS [12, 15, 16]. Although there have been a great deal of research coping with the LBP in the literature, the prediction of the LBP using the fuzzy logic has not been investigated yet. Therefore, the main aim of this study is predict the intensity of LBP using the fuzzy logic algorithm in terms of the VAS value obtained subjectively and the skin resistance measured objectively.

2. Material Methods and Study Design

One hundred and sixty-nine subjects (110 LBP patients, 59 healthy subjects) from Dumlupinar University Hospital, Physical Therapy and Rehabilitation Department, in 2008. The study had local research and ethics committee approval and all the subjects were given written consents.

The skin resistance was recorded with two surface electrodes by the Digital Multimeter (DT-9923B) tool from the lumbar paravertabral area (both left and right sides) while the subjects are in prone position. Two carbon electrodes were placed over paravertabral musculature of lumbar vertabra (L5) and 15 cm above it and direct current (5.5 volt) was applied between the two silver-silver chloride electrodes.

Statistical Analysis SPSS 15.0 for Windows statistical program was accepted for all statistical analyses. The results were presented as mean ± SD. Statistical evaluation of the data was performed with Independent-Samples t-test for comparison between the two groups. Findings with an error probability value of less than 0.05 were considered as statistically significant.

Receiver operating characteristic (ROC) curves and the area under the curve (AUC) were determined for all groups of the intensity of the LBP. The AUC values are reported with the 95% confidence interval (95% CI). The ROC analysis is used to demonstrate the classification performances and accuracy for the intensity of the LBP.

Fuzzification Process. In this approach, the VAS values were obtained and used as the first input of fuzzification. The second input of fuzzification was the skin resistance value. A flow chart of the algorithm is shown in Figure 1.

Multiple measured crisp inputs first have to be mapped into fuzzy membership functions. This process is called fuzzification. A trapezoid and triangular shapes were preferred to define fuzzy membership functions. Two trapezoids and one triangular were formed using the VAS, which ranges from 0 to 10 as seen in Figure 2. Membership degrees corresponding to the VAS were calculated by using membership functions of trapezoid given by:

$$\mu(x_i)=\begin{cases}\dfrac{x_i-a}{b-a}, & a\le x_i\le b\\ 1, & b<x_i<c\\ \dfrac{d-x_i}{d-c}, & c\le x_i\le d\\ 0, & otherwise\end{cases} \tag{1a}$$

where *a, b, c* and *d* are limits of the membership function. Membership degrees corresponding to the VAS were calculated by using membership functions of triangular given by:

$$\mu(x_i)=\begin{cases}\dfrac{x_i-e}{f-e}, & e\le x_i< f\\ 1, & x_i=f\\ \dfrac{g-x_i}{g-f}, & f<x_i\le g\\ 0, & otherwise\end{cases} \tag{1b}$$

where *e, f* and *g* are limits of the membership function. For instance, in equations (1a,b) for VAS=4, V1, V2, V3 are calculated to be 0.33, 0.67, 0.0, respectively. Also, in equation (1a) for VAS=9, V1, V2, V3 are calculated to be 0.0, 0.0, 1.0, respectively.

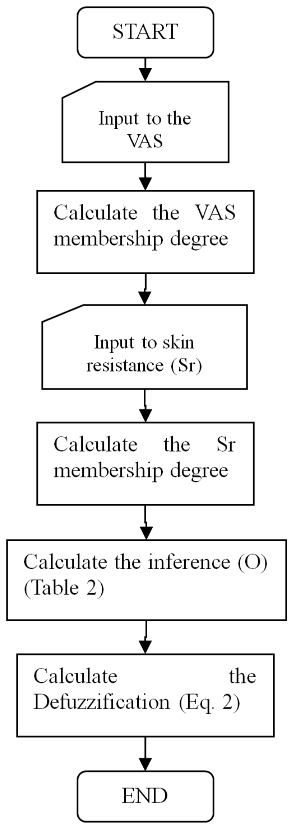

Figure 1. *A flow chart of the fuzzy logic algorithm.*

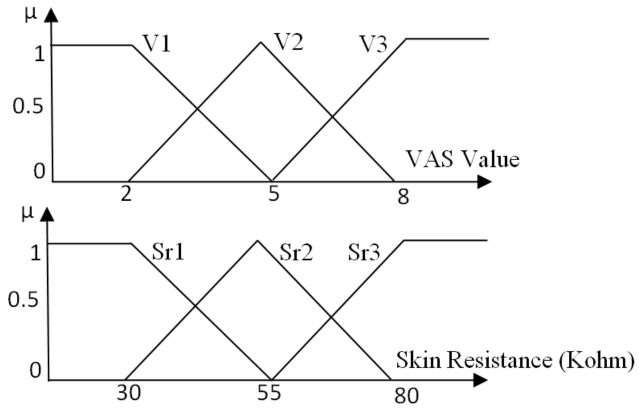

Figure 2. *Membership functions of input variables.*

Trapezoid and triangular shapes were also chosen to express the second crisp input for the skin resistance value. Three membership functions were formed for the values between 0 and 150 Kohm as seen in Figure 2. Membership degrees were calculated using equations (1a, b). For instance, in equation (1a), Sr1=0.0, Sr2=0.0 and Sr3=1.0 for the skin resistance=85 Kohm; and in equation (1b), Sr1=0.0, Sr2=1.0 and Sr3=0.0 for the skin resistance=55 Kohm.

Fuzzy Inference. The second step in fuzzy logic processing is fuzzy inference. A rule base was developed. The rule base consists of outputs of fuzzification corresponding to VAS and Sr linguistic inputs. Three linguistic outputs were used in the rule base (O1, O2 and O3) (see Table 2 and Figure 3).

Table 1. *Demographic properties of the subjects.*

Physical Properties	LBP Group (N: 110)	Control Group (N: 59)
Age, (yr)	52.5 ± 8.6	54.5 ±11.4
Height, (m)	1.7 ± 0.8	1.66 ± 0.84
Height, (m)	80 ± 11.4	74.3 ± 12.2
Sex, % (F/M)	62.7 / 37.3	49.2 / 50.8

Data are presented as Mean ± SD and N (%), LBP: Low Back Pain

Table 2. *Rule base of low back pain degree.*

	V1	V2	V3
Sr1	O1	O1	O2
Sr2	O2	O2	O2
Sr3	O2	O3	O3

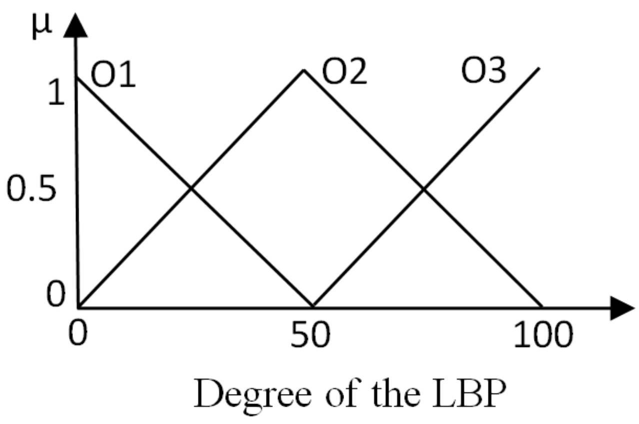

Figure 3. *Membership functions of output variables.*

Relations obtained from the rule base were interpreted using minimum operator, “and”. The outputs obtained from rule base were interpreted using maximum operator, “or”. The fuzzy rules used in the current work are as follows:

if VAS = VAS1 and Sr = Sr1 then O = O1
if VAS = VAS1 and Sr = Sr2 then O = O2
if VAS = VAS1 and Sr = Sr3 then O = O2
if VAS = VAS2 and Sr = Sr1 then O = O1
if VAS = VAS2 and Sr = Sr2 then O = O2
if VAS = VAS2 and Sr = Sr3 then O = O3
if VAS = VAS3 and Sr = Sr1 then O = O2
if VAS = VAS3 and Sr = Sr2 then O = O2
if VAS = VAS3 and Sr = Sr3 then O = O3

where 9 outputs of the VAS and Sr were available.

Defuzzification. The outputs of the inference mechanism are fuzzy output variables. The fuzzy logic controller must convert its internal fuzzy output variables into crisp values so that the actual system can use these variables. This process is called defuzzification. One can carry out this operation in different approaches. One of the most common approaches is the height method. In this method, the centroid of each membership function for each rule is first evaluated. The final output COG is then calculated as the average of the individual centroid, weighted by their heights as given by:

$$COG(x) = \frac{\sum_{x=a}^{b} \mu_A(x).x}{\sum_{x=a}^{b} \mu_A(x)} \tag{2}$$

where $COG(x)$, $\mu_A(x)$ and x stand for defuzzification output, minimum/maximum value of membership degree of input values and crisp output value, respectively. The output membership functions, O1, O2 and O3 were converted to LBP degrees, which were between 0 and 100 (Figure 3).

3. Results

The intensity level of the LBP measured from the left/right paravertabral sides and the intensity of the LBP predicted using the fuzzy logic algorithm values have been compared as seen in Table 3. There is a statistically significant difference between the intensity level of the LBP and the control groups in both $Fuzzy_{right}$ and $Fuzzy_{left}$ approaches as is the case in the diagnosis of physicians ($P<0.001$). However, there is no statically significant difference between the results for the left and right sides predicted using the fuzzy logic algorithm ($P>0.05$). As a result of these findings, use of the developed software can be used to successfully diagnose the LBP.

When the ROC curve was considered in Figure 4, it was shown that the intensity of the LBP for both right and left sides can be successfully classified using the proposed fuzzy logic software (Area under the curve; $Fuzzy_{right}$= 0.894, $Fuzzy_{left}$=0.869).

Table 3. *A comparison with the healthy control and the LBP groups in terms of the fuzzy logic results.*

Side	Groups	N	Mean±SD	P	
Fuzzyright	LBP Group	110	67.98±28.43	P<0.001	P>0.05
	Control Group	59	18.52±23.81		
Fuzzyleft	LBP Group	110	65.30±29.96	P<0.001	
	Control Group	59	20.46±26.52		

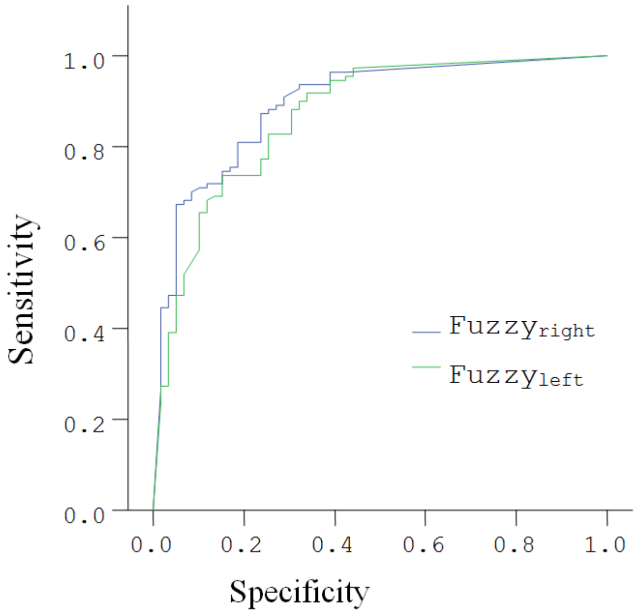

Figure 4. *The ROC curve: The intensity of the LBP for the right and left paravertabral sides using the fuzzy logic algorithm.*

4. Discussion

In this study, fuzzy logic software evaluating the intensity level of LBP objectively has been developed. In addition, the developed system has been justified to predict the intensity level of the LBP by using subjective VAS value and objective data of skin resistance. Correlation of the results delivered by the software has been found to be excellent. Moreover with the software, the intensity level of the LBP can satisfy to be followed differences before and after treatment objectively. The developed fuzzy logic algorithm has also been found to be able to identify the healthy and LBP subjects. At the same time, since it is non-invasive, there is no requirement for any surgical operation to diagnose the patients. Thus instead of the VAS method which is a subjective method, the presented objective method may be used for the scaling of the LBP.

Similarly, in another study of authors, they worked to predict the intensity of LBP using the Artificial Neural Network (ANN) and Adaptive Neuro-Fuzzy Inference System (ANFIS). Their study demonstrated that expert systems very similar to real data (R^2=0.934 for both the ANN and ANFIS). ANN and ANFIS results seem a little more meaningful than the fuzzy results. Because neural networks provide a good performance in the analysis of nonlinear multivariate data [20].

Carregal et.al. [3] designed a system consisting of a perfusion pump guided by a fuzzy logic computer interface to regulate the perfusion of alfentanil in accordance with the patient's pain response. The system was also equipped with a safety device that halted perfusion in case of desideration, bradypnea or heart rate or blood pressure variations greater than 25%.

Shieh et al. [13] used a novel fuzzy pain demand (FPD) index derived from the interval of each bolus of patient-controlled analgesia designed and documented in 255 patients. They found the FPD index modeled from a fuzzy modeling algorithm to interpret the self-titration of the drug delivery can show the patients' dynamic demand and past efforts to overcome the postoperative pain.

Shamim et al. [11] utilized fuzzy logic-based fuzzy inference system (FIS) for identifying patients unlikely to improve after disk surgery and explored FIS as a tool for surgical outcome prediction by using data of 501 patients retrospectively. They reported that the FIS has a sensitivity of 88% and specificity of 86% in the prediction of patients most likely to have poor outcome after lumbosacral miscrodiskectomy.

Our designed system is effectively to predict the intensity level of the LBP objectively. As the studies carried out in the literature, our system can be used in clinical fields. On the other hand, the present system can be extended to other musculoskeletal pathologies and visceral disorders for prediction of the intensity pain level. Thus, for further studies this factor will be taken into consideration.

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