# OSTEOPOROSIS CLASSIFICATION USING FUZZY RULE BASED AND NEURAL NETWORKS

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***Abstract*** *- Most bone densitometry ultrasound devices measure only single predefined peripheral skeletal site. We propose a classification systems to study the ability of combining speed of sound (SOS) measured at multiple bone sites to differentiate subjects with osteoporosis fractures from normal subjects based on fuzzy logic and neural networks systems. Classification rates were found to be 100% for training set and ~ 97% for testing set for a dataset of 66 subjects.*

## I. INTRODUCTION

Osteoporosis is a metabolic disorder that causes loss of bone mass and strength [1]. Quantitative Ultrasound (QUS) is rapidly becoming accepted as a method of choice for the assessment of bone fracture status [2-3], primarily because it offers quick, relatively low cost results without the harmful radiation associated with other traditional techniques such as radiography, x-ray absorptiometry and computed tomography. The propagation of ultrasound through a medium, its speed, dispersion and attenuation of signal strength are strongly influenced by the physical properties of that medium [2-3]. QUS can measure the physical properties of bone through which an ultrasound signal is traveling. Ultrasound attenuation and sound speed of transmission (SOS) through bone are two major parameters that correlate with the physical property of bone.

SOS reflects a range of bone status factors, including elasticity, structure, microstructure and cortical thickness. The World Health Organization (WHO) has defined thresholds for the diagnosis of osteoporosis based on standard densitometry [3]. More than 2.5 standard deviations below the young adult mean is classified as osteoporotic; between 1 and 2.5 standard deviations below the young adult mean are considered osteoporotic. This threshold is called (T_score) and is defined as the number of standard deviations from the mean of normal young adults (between 20 and 39) and is shown in (1).

$$T\_score = (SOS(p) – \mu\ SOS\ (healthy))\ /\ SD\ (healthy) \qquad (1)$$

The WHO classifies the patient as follows:

- Osteoporotic : T_score <= - 2.5 .
- Osteopenic : -2.5 < T_score < -1.
- Normal : T_score > -1

Existing devices were used to measure the SOS at different skeletal sites (Radius, Phalanx, and MidShaft_Tibia) and compare these reading to a reference database (For each site separately) and generate the result as a T_score value for each site. The objective of this paper is to propose a method to classify the osteoporotic subject based on a global T_score value for SOS measured at three multiple bone sites, instead of having different T_score values for each bone site separately by using fuzzy logic rule based system and neural networks classification.

## II. SOS AND T-SCORES DATA SET

SOS and T-score data for three sites (distal radius, proximal phalanx and midshaft tibia) for 66 subjects were acquired separately [4]. Data were divided into 3 groups, 20 osteoporotic, 19 osteopenic, and 27 normal subjects.

## III. FUZZY RULE BASED CLASSIFICATION

Fuzzy logic (FL) is almost synonymous with the theory of fuzzy sets, a theory which relates to classes of objects with unsharp boundaries in which membership is a matter of degree [5]. Fuzzy logic has been introduced in the literature as a classification method [6].

### *A. System Design Steps:*

This system has three inputs: (SOS of radius, SOS of tibia and SOS of phalanx) and one output (Final T_Score) or final class. The following are the steps design:

1- Identify system inputs and those inputs fuzzy ranges and establish degree-of-membership functions for each range.
2- Identify outputs ranges and its membership functions.
3- Identify rules that map the inputs to the outputs.
4- Determine the method of combining fuzzy rules actions into executable "crisp" system outputs.

### *B. Step 1, Inputs Fuzzification*

The first step is to take the inputs and determine the degree to which they belong to each of the appropriate fuzzy sets via membership functions. Each input is defined by three fuzzy sets (Low, Med, and High). Gaussian shapes are defined for the inputs/output fuzzy sets. Fuzzification results are shown in figure 1 for one of the inputs.

### *C. Step 2, Apply Fuzzy Operator*

The input to the fuzzy operator is two or more membership values from fuzzified input variables. The output is a single value. Figure 2 shows example of the *max* operator used.

### *D. Step 3, Apply Implication Method*

Every rule has a *weight* (Number between 0 and 1), which is applied to the number given by the antecedent of the IF-THEN rule. Implication process is shown in figure 3. Once proper weighting has been assigned to each rule, the implication method is performed.

### *E. Step 4, Aggregate All Outputs*

In figure 4, example of three rules have been placed together to show how the output of each rule is combined, or aggregated, into a single fuzzy set whose membership function assigns a weighting for every output (T_score) value.

### *F. Step 5, Output Defuzzification*

Figure 5 shows defuzzification process taken as centroid.

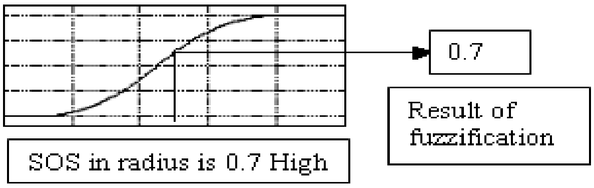


Figure 1
Inputs fuzzification

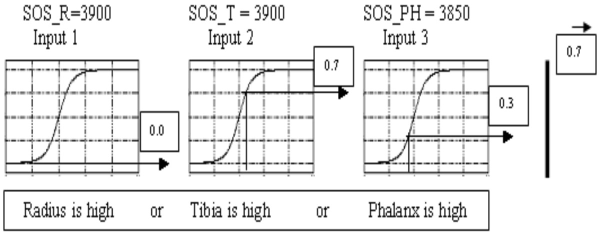


Figure 2
Applying fuzzification on the defined membership functions

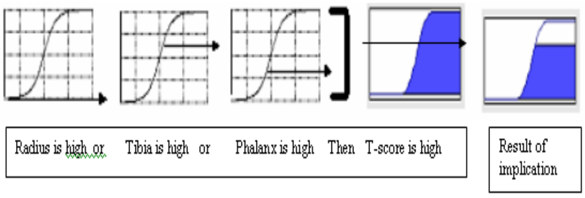


Figure 3
Fuzzy implication

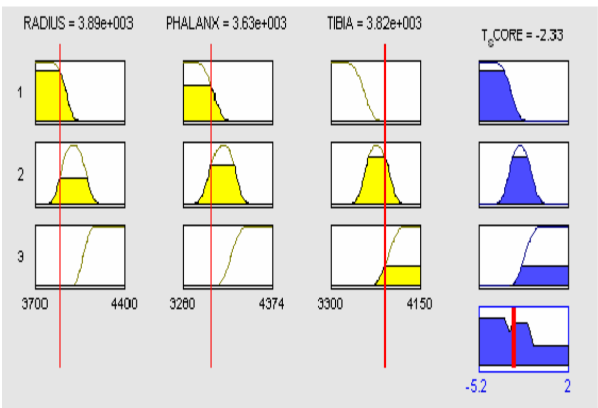


Figure 4
Rules aggregation

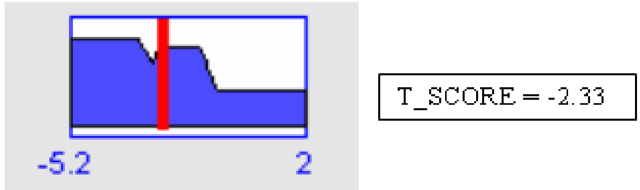


Figure 5
Output defuzzification

## IV. NEURAL NETWRORKS CLASSICATION

Multilayer backpropagation algorithm [7] is used and taking a momentum term to speed up its convergence. In this architecture shown in figure 6, the network consists of a first input layer of 6-dimensions, a second (hidden) layer of variable number of perceptrons feeding a third (output) layer of size equal to the number of classes (3 outputs binary and one is active at a time). The neural activation function shown in (1) was used.

$$f(net) = \frac{1}{1+\exp[-\lambda net]} \qquad (1)$$

Where *net is* the sum of all inputs to the neuron multiplied by their weights, and $\lambda$ is the activation constant which is set to be 1 in this architecture. The first preprocessing step for the training set is normalization between ±1 of all of the features of training and testing values. This effectively help speeding up the training by moving operating point to the linear portion of the neuron activation function, which has the highest slope.

## V. CLASSIFICATION RESULTS

Samples of 66 acquired dataset are shown in table 1. First column is SOS and second one is its associated single T-score. The fuzzy rule based system shown in figure 7 was applied to 66 subjects (20 Osteoporotic, 19 Osteopenia, and 27 Normal). Data were divided into training set (12 Osteoporotic, 9 Osteopenia,12 Normal) to generate fuzzy rules and testing set (8 Osteoporotic, 10 Osteopenia, 15 Normal) to test the capability of the inference system to get the output class. Training results were found to be 100 % and is shown as a confusion matrix format in table 2. Test results were found to be 96.96 % and are shown in table 3.

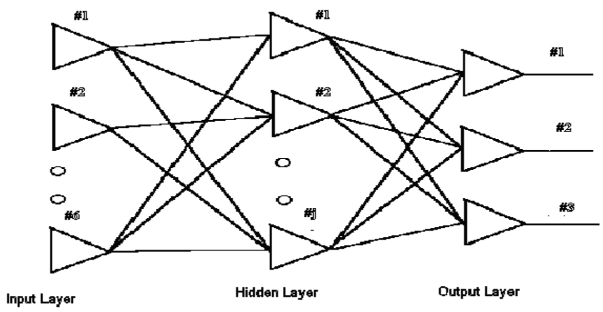


Figure 6
Neural network architecture for multilayer back propagation network

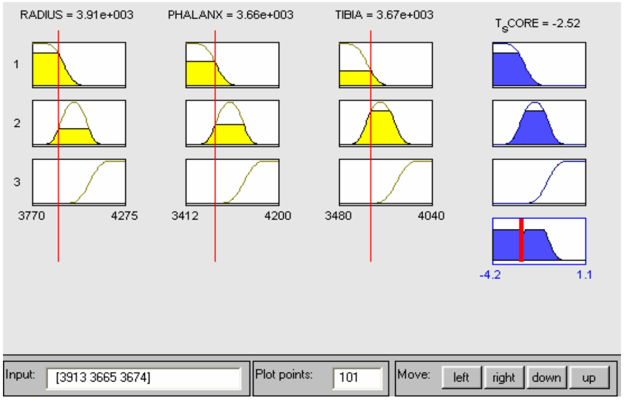


Figure 7
MATLAB output of the designed FIS system for osteoporosis diagnosis.

Table I
Sample Results of FIS

| radius | | Phalanx | | Tibia | | Final T_score | Actual | Classified |
|---|---|---|---|---|---|---|---|---|
| 3770 | -4.171 | 3400 | -4.1601 | 3480 | -4.0217 | -3.24 | Osteoporosis | Osteoporosis |
| 3946 | -2.3402 | 3686 | -2.3556 | 3678 | -2.2546 | -2.31 | Osteopenia | Osteopenia |
| 4082 | -0.9255 | 3907 | -0.9612 | 3831 | -0.8892 | -0.852 | normal | Normal |

Table II
Training Confusion Matrix Result for a Fuzzy Rule Based and Neural Networks Systems

| Class | Osteoporosis | Osteopenia | Normal | Total Data |
|---|---|---|---|---|
| Osteoporosis | 12 | 0 | 0 | 12 |
| Osteopenia | 0 | 9 | 0 | 9 |
| Normal | 0 | 0 | 12 | 12 |
| | | | | 33 |

Table III
Testing Confusion Matrix Result for a Fuzzy Rule Based and Neural Networks Systems

| Class | Osteoporosis | Osteopenia | Normal | Total Data |
|---|---|---|---|---|
| Osteoporosis | 8 | 0 | 0 | 8 |
| Osteopenia | 0 | 9 | 1 | 10 |
| Normal | 0 | 0 | 15 | 15 |
| | | | | 33 |

The results of classification using multilayer backpropagation neural networks of six inputs, three output, 10 neurons in the hidden layer, 0.00059 MSE (MSE goal was 0.0001), 15000 epochs, 0.8 learning factor, 0.7 momentum factor, and sigmoidal transfer function, were found to be the same as that of FIS shown in tables 2,3. Figure 8 shows the training error curve.

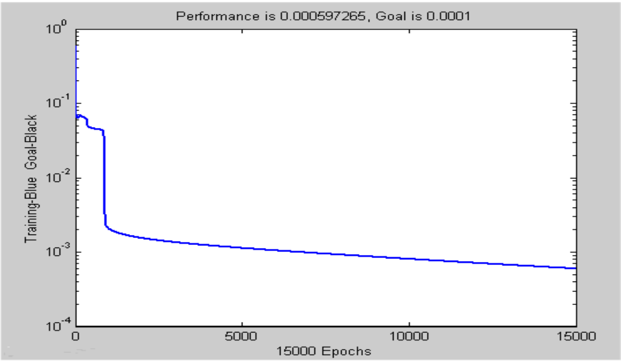


Figure 8
Neural networks training error curve.

## VI. CONCLUSIONS

Taking measurements at the three different sites and using the fuzzy rule based system or neural networks to diagnose a global osteoporosis class can improve the diagnostic efficiency to 97%. This result suggests implementing either of these systems in the ultrasound bone densitometry devices after being investigated by a large clinical database.

## VII. ACKNOWLEDGMENTS

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