A Fuzzy Expert System Design for Diagnosing Osteoporosis Based on Mandibular Cortex Measurement on Dental Panoramic Radiographs

Agus Zainal Arifin, Akira Asano, Akira Taguchi, Takashi Nakamoto, Masahiko Ohtsuka, Mikio Tsuda, Yoshiki Kudo, and Keiji Tanimoto

***Abstract*—In this paper we present a fuzzy expert system for diagnosing osteoporosis based on mandibular cortical width and shape measurement on dental panoramic radiographs. We proposed a fuzzy thresholding method to find out optimal cut off threshold for input variables to provide optimal fuzzy membership functions. This system allows the dentists to determine the important rules and provides fuzzy membership functions supporting those rules so as to be a stable and robust computer-aided diagnosis in identifying postmenopausal women with low skeletal bone mineral density (BMD). We achieve sensitivity and specificity 86.7% and 65.7%, respectively. These results indicate that this system is an effective method in identifying a large number of postmenopausal women with suspected low skeletal BMD.**

I. Introduction

Osteoporosis is one of the most common disorders with substantial morbidity rates, increased medical cost, and high mortality risk in the elderly [1]. These risks may be prevented if individuals suspected with low skeletal bone mineral density (BMD) can be identified early. The early detection may lead those individuals to have well treatment to avoid the fracture. BMD can be assessed at lumbar spine and femoral neck using dual-energy x-ray absorptiometry (DXA).

However, this equipment is too limited to identify a large number of postmenopausal women with suspected low skeletal BMD [2]. It is likely that dental panoramic radiographs are taken frequently when some body visiting to have dental caries. Several studies indicated that mandibular cortical width measurements and cortical shape analysis based on dental panoramic radiographs, may be usefull for identifying postmenopausal women with low skeletal BMD [3]. That is superior to the results by independent applications of our previous methods based on cortical width measurement only and shape measurement only.

Our previous study suggests the usefulness of simple visual estimation of the mandibular inferior cortex width for identifying postmenopausal women with low skeletal BMD [4]. Cortical width less than or equal to the specified cut off threshold is considered as having low skeletal BMD, otherwise as having normal skeletal BMD. Devlin and Horner suggested the cutoff threshold of 3 mm (or less) cortical width as the most appropriate threshold for referral for bone densitometry in Caucasian postmenopausal women [5]. Klemetti et al. determined the cutoff threshold of 4 mm cortical width with sensitivity and specificity are 37% and 85%, respectively [6]. In our previous study, we determined the optimal cutoff threshold of 4.5 mm by choosing the risk-index range corresponding to a sensitivity of approximately 90% for cortical width that manually measured by one oral radiologist [7].

Furthermore, we have developed a computer-aided system in the digital panoramic radiography system which can semi automatically measure the cortical width precisely [8]. The cortical width measured with our system has been compared with skeletal BMD. These correlations were similar with those between cortical width manually measured by oral radiologist and skeletal BMD. The cutoff threshold of cortical width was 3.09 mm. Since the low value of cortical width corresponds to the low skeletal BMD, better definition of low and high group is needed for further applications.

Another study indicates that women with inferior cortical erosion had higher bone turnover and high risk of low skeletal BMD than women with a normal cortex [9]. We also developed a computer-aided diagnosis (CAD) system that automatically determines mandibular cortical erosion for identification of postmenopausal women with low skeletal BMD [10]. Segment analysis on an area of interest generates several segments with different sizes correspond to the erosion in the inferior cortical bone. A set of decision rules are then applied to segments which considered as non-noise segments to identify individual with low skeletal BMD.

The problem emerged in the cortical width and segment analysis actually is similar, i.e. to find out qualitative criteria to determine the low skeletal BMD. Fuzzy rule-based structure is often used to model systems in an input/output

A. Z. Arifin is with the Department of Information Engineering, Graduate School of Engineering, Hiroshima University, Japan and the Department of Informatics, ITS Surabaya, Indonesia (e-mail: agusza@hiroshima-u.ac.jp).

A. Asano is with the Division of Mathematical and Information Sciences, Faculty of Integrated Arts and Sciences, Hiroshima University, 1-7-1, Kagamiyama, Higashi-Hiroshima, 739-8521, Hiroshima, Japan (Tel./Fax. 81-82-424-6476, e-mail: asano@mis.hiroshima-u.ac.jp).

A. Taguchi is with the Department of Oral and Maxillofacial Radiology, Hiroshima University Hospital, Japan (e-mail: akiro@hiroshima-u.ac.jp).

T. Nakamoto, M. Ohtsuka, and K. Tanimoto are with the Department of Oral and Maxillofacial Radiology, Graduate School of Biomedical Sciences, Hiroshima University, Japan (e-mail: {tnk, otsuka, kg}@hiroshima-u.ac.jp).

M. Tsuda and Y. Kudo are with the Department of Obstetrics and Gynecology, Division of Clinical Medical Science, Graduate School of Biomedical Sciences, Hiroshima University, Japan (e-mail: {mtsuda, yoshkudo}@hiroshima-u.ac.jp).

sense, due to its capability of description and prediction [11]. Fuzzy rules in this case are provided by human experts, i.e. oral radiologists by means IF-THEN rules.

In this paper, we propose a fuzzy thresholding method to define two linguistic variables denoted as low and high for the input variables of fuzzy rule-based classifier for combining the cortical width and shape analysis in diagnosing osteoporosis. The decision rule of the fuzzy expert system involves two fuzzy membership functions of input variables and two fuzzy membership functions of one output variable.

II. INPUT VARIABLES

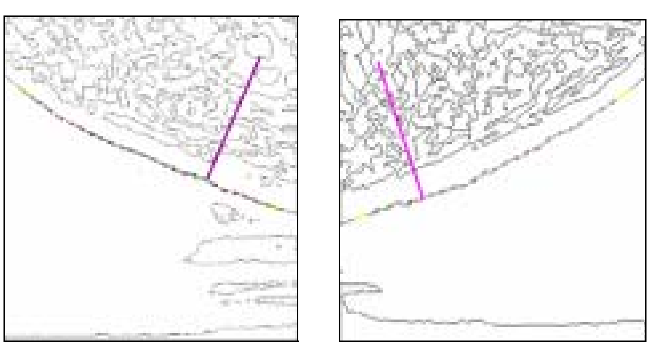
Input variables used in this system are based on mandibular cortical width and shape measurement of panoramic radiographs taken from 100 postmenopausal women who visited our clinic between 1996 and 2001 for BMD assessment.

A. Cortical Width

We developed a computer-aided system for measuring the cortical width of the lower border of the mandible below the mental foramen on panoramic radiographs [8]. This measurement as shown in Fig. 1 is semi automatically, because oral radiologists assisted to determine the position of the mental foramen on the original digitized image. Manual assistance is needed again on the pointing out the trabecular bone inside the area of interest which has been enhanced to be binary image.

There is a statistically significant correlation between the mean cortical width of both right and left side measured by the system and BMD of the lumbar spine ($r=0.50$, $P<0.001$). The optimum cut off threshold is defined by choosing the risk-index range corresponding to a sensitivity of approximately 90%. Cortical width less than or equal to the specified cut off threshold is considered as having low skeletal BMD, otherwise as having normal skeletal BMD.

The next section will define the membership function of low and high cortical width variables that correspond to the low and normal skeletal BMD.



(a) (b)

Fig. 1. Cortical width measurement on left side (a) and right side (b).

B. Cortical Shape

We have also applied a set of image processing steps for extracting segments along the endosteal margin of cortex distally from mental foramen [10]. The segments which are considered as noise-free are collected and their sizes are analyzed to distinguish normal from cortical erosion.

In this paper, we have also removed all segment considered as noise and derived some statistically measurement of segments size, including minimum, average, and maximum of segments size, as well as the number of segments. The first two features have distribution that shown slightly difference between normal and low skeletal BMD, while the rest features have the distribution of normal and now skeletal BMD data, which shared almost all of segments size. Thus, the minimum size and average size of segments are selected to be the input variables as well as the cortical width.

III. THE PROPOSED FUZZY THRESHOLDING METHOD

The problem considered in this paper may be stated in a precise way as that of finding a proper configuration of fuzzy membership function from the available training set. It is first necessary to know how many fuzzy membership function each cortical parameter has. Determination of an optimum cut off threshold by the previous studies in identifying postmenopausal women with low skeletal BMD indicated the importance of defining two different classes.

Thresholding is a simple but effective tool for separating data into two non-overlapping sets. Since thresholding is a well-researched field, there exist many algorithms for determining an optimal threshold of the image. An exhaustive survey of thresholding methods and their categorization exists in literature [12]. Several fuzzy thresholding methods have attempted to minimize the measure of fuzziness from a given histogram which contained unknown mixed distribution of two classes. The measurement can be obtained from entropy, index of fuzziness, and index of nonfuzziness [13].

This paper proposes a novel fuzzy thresholding method on the basis of histogram by minimizing a criterion function in which the index of fuzziness of a given partition is measured. Since we have knowledge about the skeletal BMD information in the training data, we need an index of fuzziness measurement method which able to involved this benefit.

Our purpose is then to threshold the cortical width, minimum and average size of segments obtained from 100 available data of postmenopausal women which have been classified as low and normal skeletal BMD. The method proposed in this paper, consists of first establishing two linguistic variables {low, normal} modeled by two fuzzy sets. In the second step, we assign each cortical measure with membership value to each fuzzy set, when a specific cortical measure used as a cut off threshold. In the same time, we measure index of fuzziness of each fuzzy set.

Finally, we define a criterion function that minimizes fuzziness of both fuzzy sets to obtain an optimal cut off threshold by which fuzzy membership function of L and N can be determined. It is interesting to point out that the determined cut off threshold is not merely used to split two fuzzy sets, but to provide two fuzzy membership functions that correspond to low and normal skeletal BMD fuzzy sets which are needed in the fuzzy expert system.

In the implementation of the histogram thresholding method on a basis of fuzziness degree comparison, we shall assume:

1. A given histogram consists of two fuzzy sets corresponded to the normal and low skeletal BMD, which are computed after determining a specific cut off threshold.
2. The membership degree of the least cortical measure achieves the maximum value for the low skeletal BMD fuzzy set and the minimum value for the normal skeletal BMD fuzzy set.
3. The membership degree of the highest cortical measure achieves the maximum value for the normal skeletal BMD fuzzy set and the minimum value for the low skeletal BMD fuzzy set.

A. Fuzzy Membership Function

Instead of the crisp deterministic assignment of a cortical parameter to a class, fuzzy thresholding method provides soft description of the classes, where each cortical parameter is assigned a membership value in each of classes. Application of fuzzy set theory may incorporate the ambiguity in measurement as well as separation.

Let us define two linguistic variables {low, normal} modeled by two fuzzy sets of X, denoted by L and N, with fuzzy membership function denoted by $\mu_L(x_i)$ and $\mu_N(x_i)$, respectively. The models reflect the compatibility measure of each cortical parameter in low and high regions.

These fuzzy sets are formally defined as
$L = \{(x_i, \mu_L(x_i))\}$ and $N = \{(x_i, \mu_N(x_i))\}$, where $x_i \in X$.
Given the minimum and maximum value are x_{min} and x_{max}, respectively, and the cut off threshold is t, then based on the assumption 2, we used Z-function for fuzzy sets L and S-function for fuzzy sets N. Since the fuzzy membership functions change with the change of parameter t which assigned with any values ranged from x_{min} and x_{max}, these definitions are modified as
$L = \{(x_i, \mu_{L,t}(x_i))\}$ and $N = \{(x_i, \mu_{N,t}(x_i))\}$, where $x_i \in X$
Then the fuzzy membership functions are defined as

$$\mu_L(x,t) = Z(x;t,x_{\min},x_{\max}) \tag{1}$$
$$= \begin{cases} 1, & x \le x_{\min} \\ 1-2\{(t-x)/(t-x_{\min})\}^2, & x_{\min} < x \le (t+x_{\min})/2 \\ 2\{(t-x)/(t-x_{\min})\}^2, & (t+x_{\min})/2 < x < x_{\max} \\ 0, & x \ge t \end{cases}$$

$$\mu_N(x,t) = S(x;t,x_{\min},x_{\max})$$
$$= \begin{cases} 0, & x \le t \\ 2\{(x-t)/(x_{\max}-t)\}^2, & x_{\min} < x \le (t+x_{\max})/2 \\ 1-2\{(x-t)/(x_{\max}-t)\}^2, & (t+x_{\max})/2 < x < x_{\max} \\ 1, & x \ge x_{\max} \end{cases}$$

Parameter t which controls the S-function and Z-function is assigned with any possible value between x_{min} and x_{max}. Each assignment of parameter t and computation of fuzzy membership value of each cortical parameter in fuzzy subsets L and N will be followed by measurement of fuzziness. This measurement will reflect the goodness of selecting a particular value as the cut off threshold.

B. Fuzziness Measurement

In the training set, we have already classified the data into two groups labeled as low and normal skeletal BMD. Our aim is to classify the ill-defined group of cortical measure into one of the defined groups by evaluating its membership value to the ordinary groups. If we have assigned a membership value, then we have to answer how fuzzy is the groups with respect to the available known groups. This fuzziness corresponds to the membership value of the rightly classified members compensated by the membership value of the wrongly classified members.

Let X_L and X_N be the universe of cortical measure that have

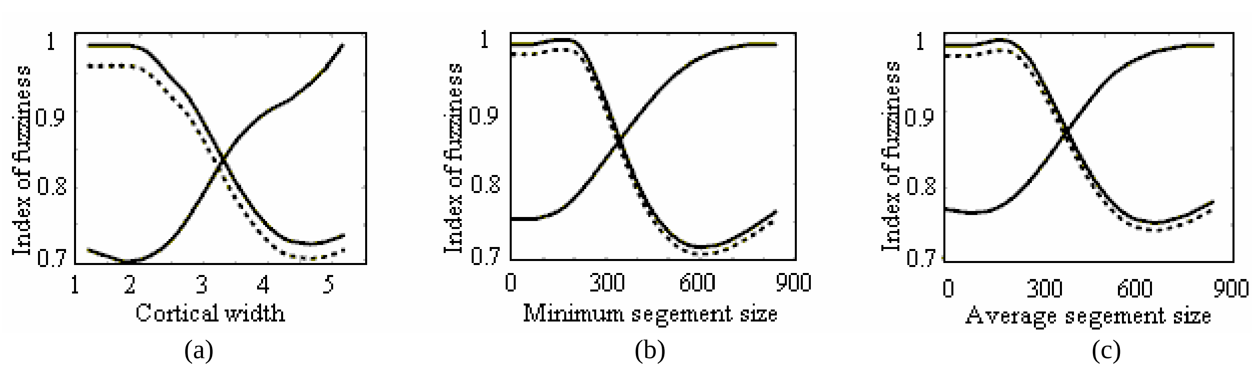


Fig. 2. Index of fuzziness measured based on membership values of the rightly classified members compensated by the membership value of the wrongly classified members for cortical width (a), minimum segment size (b), and average segment size(c). The decreasing and increasing lines correspond to low and normal skeletal BMD, respectively, where the decreasing lines have been normalized from the original ones (dashed line). The criterion function achieved least value at the intersection point at which the optimum cut off threshold is selected.

been classified to low and normal skeletal BMD, with a generic element denoted by x_{Li} and x_{Ni}, respectively. Then the index of fuzziness $\gamma_L(t)$ for fuzzy sets L and $\gamma_N(t)$ for fuzzy sets N should be measured according to the defined group of each data. Such functions are defined as

$$\gamma_L(t) = \left(\frac{\sum_{x \in X_L} (1 - \mu_L(x,t))}{|X_L|} + \frac{\sum_{x \in X_N} \mu_L(x,t)}{|X_N|} \right) / 2, \tag{2}$$

$$\gamma_N(t) = \left(\frac{\sum_{x \in X_N} (1 - \mu_N(x,t))}{|X_N|} + \frac{\sum_{x \in X_L} \mu_N(x,t)}{|X_L|} \right) / 2,$$

where $|X_L|$ and $|X_N|$ respectively denote the number of X_L and X_N member in the training set. Index of fuzziness $\gamma_L(t)$ tend to decrease, while $\gamma_N(t)$ tend to increase, with the incremental value of t.

One of index of fuzziness needs to normalize so as to compare and find the intersection point at which both indexes of fuzziness achieve the most similar value. Normalization is done by find out normalization factor α computed as

$$\alpha = \frac{\gamma_N(x_{\max})}{\gamma_L(x_{\min})} \tag{3}$$

and modifying all values in the index of fuzziness $\gamma_L(t)$.

C. Criterion Function

The optimal cut off threshold T can be determined by searching for the value so that criterion function $J(t)$ is minimum. That is

$$T = \arg\min_{t \in X} J(t), \tag{4}$$

where

$$J(t) = |\gamma_N(t) - \alpha.\gamma_L(t)|.$$

The final result of this steps is T which will be used for defining fuzzy membership function of fuzzy sets L and N as defined in Eq.(1) with parameter t is assigned with T.

Since we have three variables composed the cortical measures, such thresholding method is applied to each variable to obtain T_{cw}, T_{min}, and T_{avg} which correspond to the optimal cut off threshold of cortical width, and minimum and average segments size, respectively as shown in Fig. 2. This figure illustrates how the indexes of fuzziness plotted and normalized. Note that the original index of fuzziness for fuzzy sets L which are plotted as dashed line has been normalized with α and the normalized lines are shown above the original one. The fuzzy membership functions then can be defined as the previous defined function by replacing t with the corresponding T as

$$\begin{aligned} \mu_{CL} &= Z(x; c_{min}, T_{cw}), \\ \mu_{CH} &= S(x; T_{cw}, c_{max}), \\ \mu_{ML} &= Z(x; m_{min}, T_{min}), \\ \mu_{MH} &= S(x; T_{min}, m_{max}), \\ \mu_{AL} &= Z(x; a_{min}, T_{avg}), \\ \mu_{AH} &= S(x; T_{avg}, a_{max}), \end{aligned} \tag{5}$$

where fuzzy membership functions μ_{CL} and μ_{CH} for cortical width, μ_{ML} and μ_{MH} for minimum size of segments, and μ_{AL} and μ_{AH} for average size of segment, respectively correspond to linguistic variables low and high. Parameter values of c_{min} and c_{max} for cortical width, m_{min} and m_{max} for average size of segments, a_{min} and a_{max} for average size of segments, respectively, are obtained from minimum and maximum values of the corresponding variables.

IV. Fuzzy Expert System

A fuzzy system has involved two different phases, specifying the structure and establishing the parameters defined the fuzzy system [14]. The specification of its structure concerned with determining the number of membership function in the input and output subspaces and constructing a set of rules, as well as fuzzy expert method to be used. In general, these rules are provided by a human expert, i.e. oral radiologists in this diagnosis.

We consider fuzzy expert system to solve the problem of estimating skeletal BMD as low or normal based on the cortical parameter values. In this case cortical width and shape values have been calculated. Cortical shape consists of minimum and average size of segments composed cortex distally from mental foramen. The fuzzy membership functions for these three input variables have been defined in two linguistic variables, low and high, while the output is defined as two linguistic variables, low and normal skeletal BMD.

Now, we need a set of rules by which the fuzzy expert system will be able to act as a stable and robust CAD for identifying individual with low skeletal BMD. This system should be able to involve knowledge from the expert, i.e. oral radiologists so that its functionality should be understood clearly by the expert.

The following fuzzy rules may accurately reflect the diagnosis of low and normal skeletal BMD:

1. IF cortical width is low AND minimum size of segments is low AND average size of segments is low THEN it indicates low skeletal BMD.
2. IF cortical width is high THEN it indicates normal skeletal BMD.
3. IF minimum size of segments is high AND average size of segments is high THEN it indicates normal skeletal BMD.

The output of this system is the class of skeletal BMD, i.e. normal and low skeletal BMD. We assigned Normal and Low BMD as two specific classes, with the value of 0 and 10, respectively. Hence the output of this system will be ranged between 0 and 10. Indeed the default margin is 5, so that output less than 5 are classified as low skeletal BMD, otherwise as Normal.

V. Experimental Results

We have extracted three input variables from panoramic radiographs taken from 100 postmenopausal women and one output variable as the result of skeletal BMD assessment by

DXA scanner. We select randomly 50 of 100 data as the training set to define the fuzzy membership functions. Based on this training set, the optimum cut off thresholds of T_{cw}, T_{min}, and T_{avg} that found at the intersection point as shown in Fig. 2 are 3.1, 333.5, and 313.5, respectively. These cut off thresholds are used as the parameters for six fuzzy membership functions as shown in Eq. (5).

Three rules defined before applied to the rest of the data that assigned as the test set. Sensitivity and specificity are then computed from identification results based on the real class of the individual which defined by the result of skeletal BMD assessment.

In the experiment II, 50 data in the test set are used as the training set, while the rest 50 data which were used as the training set, now are used as the test set. Table 1 records the result of the experiment I and II.

Sensitivity and specificity computed from the experimental results shown in Table I are 86.7% and 65.7% for the experiment I, and 80% and 82.5% for the experiment II, respectively. This parameter evaluation results between the experiment I and II seem to be similar. This implies that the system is robust and stable for the different subjects.

TABLE I
NUMBER OF SUBJECTS WITH NORMAL AND LOW SKELETAL BMD

	Experiment I		Experiment II	
	Normal	Low BMD	Normal	Low BMD
Prediction:				
Normal	23	2	33	2
Low BMD	12	13	7	8

In comparison with the previous studies which used 100 data of cortical width as the training set and test set, the sensitivity and specificity were 88% and 58.7%, respectively. In this experiment, if we use all data as the training set and test set, then the sensitivity and specificity are 84% and 74.7%, respectively. This performance evaluation results may be difficult to compare due to different sensitivity level.

TABLE II
NUMBER OF SUBJECTS COMPARED WITH THE PREVIOUS STUDY

	This system		The previous study	
	Normal	Low BMD	Normal	Low BMD
Prediction:				
Normal	52	3	43	3
Low BMD	23	22	32	22

For the aim of comparison, with respect to similar sensitivity, the output was forced to have sensitivity of 88% as achieved by the previous study. Forcing to this level can be done by tuned the assigning class of output. The default margin defined in the previous section is 5. Therefore if this margin is shifted higher, then more individuals will be classified as Low BMD. In this case, margin of 6.01 is selected to obtain sensitivity of 88%. Finally, the performances evaluations of this system show sensitivity of 88% and specificity of 69.3% as illustrated in Table II. Note that even we forced the system to achieve similar number of true positive subjects (22 subjects), but this system achieved more true negative (52 subjects) than the previous study (43 subjects).

VI. FUTURE WORKS

In conclusion, incorporating more input variables with suitable definition of fuzzy membership function will obtain better performance in identifying postmenopausal women with suspected low BMD. Indeed, this combination needs an appropriate expert system which stable for diagnosing new individuals.

Since parameters of fuzzy membership functions correspond to the cortical width and cortical segment analysis have been established in this system, identifying a large number of postmenopausal women with suspected low skeletal BMD is not a hard effort. This work suggests that this fuzzy-based computer-aided system is an effective method in identifying postmenopausal women with suspected low skeletal BMD.

In this paper, we also have found that it may be still possible to involve more variables such as other cortical parameters, trabecular pattern analysis, etc. in which linguistic variables may need to extend. Incorporating more inputs with more linguistic variables may also need more complex of fuzzy rules definition. Hence, we need to support the oral radiologist with an automatic generation of rules from training examples.

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