Continuous Measurement of the Mandibular Cortical Bone in Dental Panoramic Radiographs for the Diagnosis of Osteoporosis using a Clustering Algorithm on Histograms

M. S. Kavitha, Liang Li, Febriliyan Samopa, Akira Asano, and Akira Taguchi

Abstract—This study aimed to realize a newly developed method of continuous measurements of the cortical width of the lower border of the mandible, between the upper and lower margins of the cortical bone to identify women with low bone mineral density (BMD) or osteoporosis. An automatic clustering algorithm is applied to obtain a robust estimate of the cortical width. This continuous measurement method provides more accurate cortical width than the conventional one-point method. The system’s efficacy in identifying low BMD at the lumbar spine and femoral neck in 100 postmenopausal women (≥50 years) with no history of osteoporosis was evaluated. The mandibular cortical width below the mental foramen was measured by enhancing the original image of the panoramic radiograph, determining cortical boundaries and evaluating the distance between boundaries continuously, by applying the clustering algorithm to a significant portion of the histogram. It is experimentally shown that the improved sensitivity and specificity provided more stable and significant diagnostic accuracy than the conventional one-point method.

I. INTRODUCTION

Osteoporosis is considered a major health problem in the elderly population in Japan as well as worldwide. It is characterized by the loss of bone mass accompanied by structural alteration of the bone and increased incidence of fractures, especially of the hip [1]. The risk of fracture has been correlated with bone mineral density (BMD), and assessment of BMD by dual-energy X-ray absorptiometry (DXA) is considered the gold standard for identifying asymptomatic individuals with osteoporosis [2]. Identifying asymptomatic individuals is an important strategy in controlling the increase in morbidity, mortality and medical costs worldwide [2, 3]. BMD assessment is considered a reliable method of identifying individuals at risk, especially postmenopausal women who are at a higher risk than premenopausal women. However, the availability of DXA scanning facilities is too limited to identify a large segment of postmenopausal women with undetected osteoporosis [3, 4].

Several studies [4, 6] have indicated that manually measuring mandibular inferior cortical width below the mental foramen on panoramic radiographs is a useful indicator of skeletal BMD in postmenopausal women; dentists could identify postmenopausal women with undetected osteoporosis with the help of dental panoramic radiographs, which allow the observation of teeth and jaws at the same time. The conventional one-point method uses a computer-aided system to measure the mandibular cortical width at a single point towards the mental foramen with manual assistance [5].

In this paper, we propose a method for the continuous measurement of cortical width in some extent to allow the use of statistical operations for more stable results. We also propose the application of histogram clustering to measure cortical width instead of the simple trimmed mean for statistical operations to avoid a prior threshold setting. We experimentally show the superiority of our method in terms of efficacy for diagnosing osteoporosis compared to the conventional one-point method.

II. MATERIALS AND METHODS

A total of 531 female patients visited dental clinics for DXA measurements between 1996 and 2001. Of these 531 patients, 100 postmenopausal patients aged 50 years or above, with no previous record of osteoporosis, were randomly selected for this study. Panoramic radiographs were obtained for all subjects with their consent, and they underwent DXA measurements of the lumbar spine and femoral neck (DPX-alpha, Lunar Co., Madison, WI, USA). All subjects were selected strictly based on the following criteria: no menstruation for at least a year; not diagnosed with any metabolic bone disease (hyperparathyroidism,
hypoparathyroidism, Paget’s disease, osteomalacia, renal osteodystrophy or osteogenesis imperfecta) or cancer with bone metastasis; no significant renal impairment; not taking any medication such as estrogen that would affect bone metabolism; no hysterectomy or oophorectomy and no history of smoking or any bone destructive lesions (e.g. malignant tumours or osteomyelitis) in the mandible.

All panoramic radiographs were obtained with AZ-3000 (Asahi Co., Kyoto, Japan) at 12 mA and 15 s; kVp varied between 70 and 80, and were digitalized with the resolution of 300 dpi using a flat-bed scanner (ES-8000, Epson, Japan). Screens of speed group 200 (HG-M, Fuji Photo film Co., Tokyo, Japan) and film (UR-2, Fuji Photo Film Co., Tokyo, Japan) were used. Ten sets of duplicated films (MI-Dup: Fuji Photo Film Co.), processed by an automatic film processor (Cepros M: Fuji Photo Film Co.) were made of the 100 original panoramic radiographs for the assessment. The appearance of the mandibular inferior cortex (MIC) was bilaterally clear in the radiographs.

III. CORTICAL WIDTH MEASUREMENT

The schematic diagram of the proposed automated system is shown in Fig. 1. This system determines the region of interest, enhances the area of interest in the image, detects the inner and outer boundary of the cortex and finally measures the distance between the boundaries of the cortex using the clustering algorithm.

![Diagram of cortical width measurement](image)

A. Region of Interest Determination
   a. Contrast stretching
   b. Determining mental foramen
   c. Cropping area around mental foramen

B. Image Enhancement
   a. Thresholding algorithm
   b. High-pass filtering

C. Cortical Margin Identification
   a. Distance function
   b. Thresholding
   c. Closing and opening
   d. Distance function
   e. Inverting image
   f. Dynamic programming
   g. Masking
   h. Inserting disc
   i. Identifying upper and lower boundaries

Fig. 1 Schematic diagram for measuring cortical width.

The area included a 300 x 300-pixel in the lower border of the mandible below the mental foramen on both right and left sides from the digitized panoramic radiographs were considered as a processing region of interest. Since some of the original images are in very low contrast, we used a typical contrast stretching algorithm [5] that stretches the appropriate range of intensity values in the area around the mental foramen as shown in Fig. 2. The original radiograph has a resolution of 1744 × 3158 pixels. Therefore, it is important to determine the area of interest to reduce computation time.

Fig. 2 Digitized dental panoramic radiograph showing two boxes corresponding to the area below the mental foramen on the right and left sides of the mandible.

B. Image Enhancement

Images were enhanced to distinguish the cortical bone from trabecular tissue and background. The first step in enhancement was using the clustering threshold algorithm [5], which separates the image pixels into foreground and background where the threshold determination is based on the intra- and inter-class variance of the pixel values. As shown in Fig. 3, we multiply this binary image with the original image, which preserves all grey levels considered as foreground and removes all gray levels considered as background. Applying high-pass filtering was the final step of this process; it is useful in extracting the edges and sharpening the images as shown in Fig. 4. Since direct application of high-pass filtering to the original image is suppresses some needful information, average filter (low-pass filter) is used to generate the low frequency image. The resultant image is subtracted from the original image lead to the image consisting of high frequencies. This resultant grayscale image is binarized using a threshold related to the mean of all the pixel values in the image.

C. Cortical Margin Identification

Since the margins of the cortex appeared uneven (showed defects) and porous, it is necessary to validate the appropriate cortical margins. The eight neighbourhood distance function (ENDF) is useful for iteratively analysing the objects via forward and backward scanning. The value of every pixel in the ENDF image was equal to the distance from that pixel to the boundary of the object pixel. All pixels with a value less
than 10% of the maximal value were removed to filter the
cortical bone width at more than 20 pixels, and then cluster
thresholding [5] was applied. The holes or unwanted objects
between the cortical boundaries are removed by
morphological closing and opening using a disk structuring
element of size 5. ENDF was applied for the second time to
the cortical boundary to determine the objects with maximum
value pixels; this represents the diameter of the cortical bone
for estimating cortical boundaries.

The pixel locations of the central axis in the cortical bone
were identified by dynamic programming [7]. We employed
the dynamic programming method proposed previously [8],
which traces the central axis in the cortical bone by finding
the maximum value pixels from left to right. This can be
achieved by calculating the maximum value in each column
from left to right and then trace back the maximum value
from right to left. It results to the optimal path thereby
estimating the pixel locations of the central axis.

Fig. 3 Binary images of the (a) right and (b) left cortex.

Fig. 4 High-pass filter images of the (a) right and (b) left cortex.

The pixel locations derived by dynamic programming were
masked with the pixel values derived from the ENDF image,
which preserves every possible pixel value with the
 corresponding positions along the cortex boundary. Thus, the
value of a pixel located on that path was assumed as the
radius of the objects. The disc was inserted by putting the
centre of the disc in the location of every pixel on that optimal
path; the radius was equal to corresponding pixel value in the
ENDF image. After disc insertion, tracing the upper and
lower boundaries of the cortex gave a final measurement of
the distance between the cortical margins.

Fig. 5 Cortical width measurement process on the right and left sides,
respectively, of the mandibular cortical bone images (a), (b) closing and
opening; (c), (d) ENDF; (e), (f) dynamic programming; (g), (h) disc insertion
D. Distance Measurement
The last step involved measuring the distance between cortical boundaries. A polynomial function of second degree was fitted to the upper cortical boundary using the least square method to approximate the boundary shape. This approximated curve was used to find the tangent lines from the upper boundary to the lower, and the cortical width at each point was measured along the tangent line as shown in Fig. 5.

E. Clustering Algorithm
This study proposed a clustering algorithm to remove some otherwise irremovable noise or objects during the continuous measurement of cortical width. Since, opening by a fixed structuring element cannot produce stable results in continuous measurement. In our previous work, we have adopted trimmed mean method to remove the false values in the continuous measurement caused by uneven illumination and other local noises. However, the trimmed mean method requires a parameter of discarding ratio, which depends on the noise rate of each image to be set in advance.

Therefore, we proposed a novel cluster number optimization method in which the ratio of element numbers between the largest and second largest cluster was adopted as the criterion.

We assumed that the most significant cluster in the histogram of the measured cortical width was correct measurement. K-means clustering algorithm [9] was adopted in this approach.

In this algorithm the optimum number of clusters $k$ is required to be decided automatically. Conventional cluster number optimization methods that consider variance or AIC (Akaike Information Criterion) value between clusters [10, 11] did not work well in this application because the aim of this application was to preserve the most significant cluster and remove the insignificant elements instead of making groups with less variance.

The optimum number of clusters and the most significant cluster were estimated by the following procedure:

1. Repeat step (2), (3) and (4) with varying $k$ from 1 to 10.
2. Cluster the histogram into $k$ clusters.
3. Calculate the element number in each cluster.
4. Calculate the ratio of element numbers between the largest and second largest cluster:

$$R_k = \frac{C_{k_{\text{max}}}}{C_{k_{\text{sec}}}}, \quad (1)$$

where $C_{k_{\text{max}}}$ is the element number of the largest cluster and $C_{k_{\text{sec}}}$ is element number of the second largest cluster.

5. The $k$ producing the largest $R_k$ is regarded as the optimum number of clusters. The cluster with the most elements is regarded as the most significant cluster.

To avoid the border effect, eight measures were removed from both the left and right sides before the clustering procedure. The experimental results are shown in Figs. 6 and 7.
Fig. 6 (Continued) (c) the result of border effect removal, and (d) the result of using the clustering method (optimized cluster number = 4).

Fig. 7 Histograms showing the result using the clustering algorithm at the left cortex: (a) the original histogram, (b) result of trimmed mean method (trimmed 10%), (c) the result of border effect removal, and (d) the result of using the clustering method (optimized cluster number = 2).
TABLE I

<table>
<thead>
<tr>
<th>Region</th>
<th>SE</th>
<th>SP</th>
<th>PPV</th>
<th>NPV</th>
<th>AR</th>
<th>LR</th>
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<tr>
<td>Right</td>
<td>92.0</td>
<td>67.0</td>
<td>47.9</td>
<td>96.2</td>
<td>73.2</td>
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<td>(56.0–100.0)</td>
<td>(42.1–100.0)</td>
<td>(84.5–100.0)</td>
<td>(64.1–100.0)</td>
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<td>(56.0–100.0)</td>
<td>(40.4–100.0)</td>
<td>(84.3–100.0)</td>
<td>(62.3–100.0)</td>
<td>(2.3–3.0)</td>
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<tr>
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<td>(69.4–100.0)</td>
<td>(3.2–3.4)</td>
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Continuous measurement using clustering algorithm

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<td>64.2</td>
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<td>(83.8–100.0)</td>
<td>(56.1–100.0)</td>
<td>(1.8–2.4)</td>
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<tr>
<td>Left</td>
<td>92.1</td>
<td>75.3</td>
<td>53.7</td>
<td>96.6</td>
<td>79.3</td>
<td>3.7</td>
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<tr>
<td>Femoral neck</td>
<td>(81.0–100.0)</td>
<td>(65.9–100.0)</td>
<td>(47.1–100.0)</td>
<td>(84.8–100.0)</td>
<td>(69.4–100.0)</td>
<td>(3.2–3.4)</td>
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Conventional method using one-point measurement [5]

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<th>NPV</th>
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<td>(1.6–2.9)</td>
<td>(1.8–2.4)</td>
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<tr>
<td>Femoral neck</td>
<td>87.5</td>
<td>56.3</td>
<td>40.4</td>
<td>93.0</td>
<td>64.2</td>
<td>2.0</td>
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<td>(1.5–2.7)</td>
<td>(1.6–2.9)</td>
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IV. RESULTS

A. Diagnostic Efficacies

The first requirement of a diagnostic test is that it measures accurately the presence or absence of a disease. Sensitivity measures the percentage of sick people who are identified as having the condition. Specificity measures the percentage of healthy people who are identified as not having the condition. Variations in the selection of the threshold or criterion value used to determine the disease diagnosis will either increase the sensitivity or increase the specificity. In this method a risk index range corresponding to the sensitivity of approximately 90% was considered to determine the optimal cut-off threshold for identifying women with low BMD. Based on this range, the optimal cut-off thresholds for the right cortical width of the lumbar spine and femoral neck were 34.3 and 36.6 pixels, respectively, and for the left cortical width of the lumbar spine and femoral neck were 37.4 and 33.6 pixels, respectively.

The sensitivity and specificity for identifying women with low BMD was calculated. The sensitivity for both the right and left cortical width of lumbar spine and femoral neck was 92%. The respective specificity for the right and left cortical width of the lumbar spine was 67% and 64%, and with femoral neck these were 55% and 75% (see Table I). The conventional one-point measurement [5] of cortical width reported that the respective sensitivity and specificity with the lumbar spine were 88% and 58.7% respectively, and those for the femoral neck were 87.5% and 56.3%, respectively. The specificity of left cortical width was significantly higher than that of the right in our study. However, we found no significant differences in sensitivity. In accuracy, some significant differences were found. Positive predictive value is the most important measure of the diagnostic test as it reflects the probability that a positive test reflects the underlying condition being tested for. The highest positive predictive value for detecting osteoporosis, with 55% of women designated at high risk of having low BMD.

Negative predictive value is the proportion of patients with negative test results who are correctly diagnosed. The high negative predictive value from 95% to 97% of women designated at low risk having normal BMD. The sensitivity of the decision rule to identify women with osteoporosis ranged from 92% to 95% and specificity from 35 to 46%. Our results of sensitivity on both sides of the mandibular cortical width using the proposed clustering algorithm is more robust diagnostic performance for identifying the high risk group for osteoporosis.

There were significant correlations between the cortical width derived from this system and BMD at the lumbar spine and femoral neck. The correlation coefficient for identifying women with low spinal BMD and femoral neck were (r=0.43, P<0.001) and (r=0.48, P<0.001) on the right side of mandibular cortical width, however, on the left side of cortical width it was (r=0.51, P<0.001) and (r=0.49, P<0.001) respectively.

A semi-automatic technique was described [12], with the significant correlation (r=0.48, P<0.001) between total hip BMD and metacarpal index of the assessment of osteoporosis, aged 75 or more in 379 elderly community-dwelling women. Our measurement of correlations on the right side of mandibular cortical width on dental panoramic radiograph with lumbar spine and femoral neck were similar to that of their study. Our measurements of PPV indicated that 54% of
those in the high risk group were correctly identified with this system, can replace the BMD testing.

B. ROC Analysis

The receiver operating characteristic (ROC) curve is a graphical plot between sensitivity vs. 1-specificity for a binary classifier system at each possible threshold value. It is mainly used for describing and comparing the accuracy of the diagnostic test. In ROC curve, the classifier boundary between classes must be determined by an optimal threshold value, which is usually selected at the upper left corner of the graph. The shape of the curve and the difference in area (Az) under the ROC curves represents a summary statistic of the ability of the diagnostic test to accurately detect the disease [13].

A high value of area under the curve represents an excellent diagnostic test, and one, which has both good sensitivity and specificity. The ROC curve goes towards the diagonal path in the graph represents a poor diagnostic test.

Here ROC curve used to calculate the area under the curve for identifying women with low spinal and femoral neck BMDs. Mandibular cortical width derived from the right side of the cortical bone using clustering method and assessed for diagnosing osteoporosis at the lumbar spine BMD gave an area under the ROC curve Az as 0.851 (95% CI=0.781-0.921) shown in Fig. 8. The same right cortical width assessed for diagnosing at femoral neck BMD gave Az as 0.830 (95% CI=0.756-0.904) shown in Fig. 9. Mandibular cortical width derived from left side of the cortical bone using clustering method and assessed for diagnosing at the lumbar spine BMD gave Az as 0.841 (95% CI=0.769-0.913) shown in Fig. 10. Likewise at femoral neck BMD gave Az as 0.863 (95% CI=0.796-0.930) shown in Fig. 11.

There was no significant difference in Az values between right and left cortical width assessed for diagnosing at lumbar spine BMD. But there was a significant difference in Az values between right and left cortical width assessed for diagnosing at femoral neck BMD. The conventional method [5] described the area under the ROC curve at the lumbar spine BMD as 0.777 and for the femoral neck as 0.803, indicating that our proposed method is an excellent diagnostic technique with a high value of the area under the ROC curve.
V. CONCLUSIONS

In this study, we proposed a newly developed clustering algorithm for the continuous measurement of cortical width in panoramic radiographs. The conventional one-point cortical measurement system is considered as a semi-automatic system and time consuming, which highly depends on professionals to do the measurement. In relation to that 2 important reasons are given below: 1. Manual assistance is needed to determine the cortical margins; 2. An expert of the dental radiology is required to define the position of the mental foramen for the final measurement of cortical width [5]. However, in our proposed clustering algorithm all operations are performed automatically, and hence, even untrained persons can use it. The improved specificity proved that measuring cortical width using the clustering algorithm could ensure better noise removal by preserving the most significant part. Performance comparison and the simplicity of this method suggest that it could be readily adopted in clinical practice.

The proposed clustering method can be considered a sufficient evidence for application in osteoporotic patients because it can easily check for a low BMD level or osteoporosis, through the accurate cortical width. However, the proposed method suffers from problems of image quality and uneven illumination. Our future challenge is to find a suitable technique to overcome these limitations.

REFERENCES
