Directional fractal signature methods for trabecular bone texture in hand radiographs: Data from the Osteoarthritis Initiative

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Purpose: To develop directional fractal signature methods for the analysis of trabecular bone (TB) texture in hand radiographs. Problems associated with the small size of hand bones and the orientation of fingers were addressed.

Methods: An augmented variance orientation transform (AVOT) and a quadrant rotating grid (QRG) methods were developed. The methods calculate fractal signatures (FSs) in different directions. Unlike other methods they have the search region adjusted according to the size of bone region of interest (ROI) to be analyzed and they produce FSs defined with respect to any chosen reference direction, i.e., they work for arbitrary orientation of fingers. Five parameters at scales ranging from 2 to 14 pixels (depending on image size and method) were derived from rose plots of Hurst coefficients, i.e., FS in dominating roughness (FS_{Sta}), vertical (FS_V) and horizontal (FS_H) directions, aspect ratio (StrS), and direction signatures (StdS), respectively. The accuracy in measuring surface roughness and isotropy/anisotropy was evaluated using 3600 isotropic and 800 anisotropic fractal surface images of sizes between 20×20 and 64×64 pixels. The isotropic surfaces had FDs ranging from 2.1 to 2.9 in steps of 0.1, and the anisotropic surfaces had two dominating directions of 30° and 120° . The methods were used to find differences in hand TB textures between 20 matched pairs of subjects with (cases: approximate Kellgren-Lawrence (KL) grade ≥ 2) and without (controls: approximate KL grade < 2) radiographic hand osteoarthritis (OA). The OA Initiative public database was used and 20×20 pixel bone ROIs were selected on 5th distal and middle phalanges. The performance of the AVOT and QRG methods was compared against a variance orientation transform (VOT) method developed earlier [M. Wolski, P. Podsiadlo, and G. W. Stachowiak, "Directional fractal signature analysis of trabecular bone: evaluation of different methods to detect early osteoarthritis in knee radiographs," *Proc. Inst. Mech. Eng., Part H* **223**, 211–236 (2009)].

Results: The AVOT method correctly quantified the isotropic and anisotropic surfaces for all image sizes and scales. Values of FS_{Sta} were significantly different ($P < 0.05$) between the isotropic surfaces. Using the VOT and QRG methods no differences were found at large scales for the isotropic surfaces that are smaller than 64×64 and 48×48 pixels, respectively, and at some scales for the anisotropic surfaces with size 48×48 pixels. Compared to controls, using the AVOT and QRG methods the authors found that OA TB textures were less rough ($P < 0.05$) in the dominating and horizontal directions (i.e., lower FS_{Sta} and FS_H), rougher in the vertical direction (i.e., higher FS_V) and less anisotropic (i.e., higher StrS) than controls. No differences were found using the VOT method.

Conclusions: The AVOT method is well suited for the analysis of bone texture in hand radiographs and it could be potentially useful for early detection and prediction of hand OA. © 2014 American Association of Physicists in Medicine. [<http://dx.doi.org/10.1118/1.4890101>]

Key words: trabecular bone, fractal signature, radiographs, hand osteoarthritis

NOMENCLATURE

Abbreviation	Description		
2D	Two-dimensional	ceil	Ceiling function
3D	Three-dimensional	CMC	Carpometacarpal
abs	Absolute value function	d_n, d_{nm}	Euclidean distances
AVOT	Augmented variance orientation transform	D, D'	Sets of directions
ANOVA	One-way analysis of variance	DFS	Directional fractal signature
b_r	Gray-scale level value in set B_{nm}	DIP	Distal interphalangeal
b'_r	Difference between gray-scale level values	DPI	Dots per inch
B_{nm}	Set of image pixels	FD	Fractal dimension
BMI	Body mass index (kg/m^2)	FD_t	Theoretical FD
		floor	Floor function
		FS	Fractal signature
		FS_H, FS_V	Horizontal and vertical FSs

FS _{Sta}	Fractal signature S _{ta} (dominating roughness direction)
HSD	Honest significant difference
<i>H</i>	Hurst coefficient
<i>i, j</i>	Indices of pixel coordinates in image and K
<i>I</i>	Image function
IP	Interphalangeal
JSN	Joint space narrowing
K	Matrix used to store image pixels
KL	Kellgren-Lawrence
<i>L_x, L_y</i>	Spatial domains
<i>L_{xy}</i>	Search region
<i>L_z</i>	Gray-scale level domain
OA	Osteoarthritis
OAI	Osteoarthritis Initiative
OARSI	Osteoarthritis Research Society International
MLE	Maximum likelihood estimator
MRI	Magnetic resonance image
<i>n, m</i>	Indices of directions and distances
<i>N_g, N_h</i>	Dimensions of a square grid (pixel)
<i>N_r</i>	Number of gray-scale level values in <i>B_{nm}</i>
<i>N_x, N_y</i>	Number of pixels in horizontal and vertical directions
<i>N_z</i>	Number of gray-scale level values
<i>N_θ, N_d</i>	Number of directions and pixels
<i>N_{dn}</i>	Number of pixels in direction <i>θ_n</i>
<i>N'_θ</i>	Number of directions in set <i>D'</i>
<i>P</i>	Set of pixels
PIP	Proximal interphalangeal
QRG	Quadrant rotating grid
<i>P_n, P'_n</i>	Set of pixels belonging to directions <i>θ_n</i> and <i>θ'_n</i>
<i>r</i>	Index of pixels belonging to <i>B_{nm}</i>
<i>r₁, r₂</i>	Inner and outer radii of search region (pixel)
<i>R_w, R_h</i>	Width and height of texture region (pixel)
<i>R</i>	Set of differences, distances and directions
RMPS	Recursive multidirectional pixel selection
ROI	Region of interest
SD	Standard deviation
sgn	Sign function
S _{ta}	Texture minor axis
S _{td}	Texture direction (°)
StdS	Texture direction signature (°)
S _{tr}	Texture aspect ratio
StrS	Texture aspect ratio signature
<i>T</i>	Statistics of differences of gray-scale level values
TB	Trabecular bone
VAR	Variance
VOT	Variance orientation transform
x , Δx	Coordinate vectors
x_θ , Δx_θ	Coordinate vectors in direction <i>θ</i>
<i>x_i, y_j, x_{nm}, y_{nm}</i>	Coordinates of image pixels
<i>z_{ij}</i>	Gray-scale level value of pixel located at (<i>x_i, y_j</i>)
<i>ρ</i>	Correlation of normals
<i>β</i>	Slope of a line

<i>θ, θ_n, θ'_n</i>	Directions in which FDs are calculated (°)
<i>θ_r</i>	Reference direction (°)

1. INTRODUCTION

The most common form of arthritis in hand is osteoarthritis (OA),¹ which is also a risk factor for developing the disease in other joints, especially in knees and hips.^{2,3} Hand OA is characterised by slow degenerative changes of articular cartilage and bones in finger joints. The changes are currently assessed primarily by visual grading of joint space narrowing and osteophytes on radiographs using hand radiograph atlases.⁴ However, the visual assessment of hand radiographs is often inaccurate because the change of cartilage volume in the joints is small and the grading requires experienced observers in order to be reproducible and also, it is not sensitive to early OA changes.^{5,6} Thus, there is an urgent need to develop methods that would allow a reliable assessment of hand radiographs for the prognosis and diagnosis of early OA.^{7,8}

Such method could be based on the analysis of trabecular bone (TB) texture selected on hand radiographs. Previous studies showed that: (i) the structure of TB changes at early stages of OA,^{9–11} (ii) it exhibits fractal properties, i.e., the self-similarity over a range of scales,¹² and (iii) radiographic technique produces 2D projections of TB, called TB texture images, which are related to the underlying 3D bone structure.¹³ Several methods have been used to quantify hand TB texture images. They include statistical methods such as second-order histogram statistics of gray-scale level values¹⁴ and co-occurrence and run-length matrices.^{15,16} However, their usefulness is limited by not accounting for the fractal properties of TB texture. Studies showed that the fractals are related to 3D bone structure.^{13,17} Therefore, a fractal approach, called a maximum likelihood estimator (MLE) was used.^{15,16} In this approach, fractal dimensions (FDs) are estimated in different directions. The dimensions are a measure of the roughness of bone texture on radiographs, i.e., higher dimension values correspond to higher roughness. Although the MLE yields useful results it does not quantify TB at individual scales in each direction. Studies showed that OA TB texture changes occur at individual scales and in different directions.¹⁸ These changes in texture could be quantified using a directional fractal signature (DFS) method, called a variance orientation transform (VOT) method.¹⁹ The method has the ability to produce fractal signatures (FSs) in many different directions. FS is a set of FDs calculated at individual trabecular image sizes (i.e., scales). The VOT method calculates Hurst coefficients (*H*) at nine scales in different directions through fitting lines to log–log plots of variances of absolute differences of gray-scale level values of pixel pairs against distances between the pixels. Having the gray-scale level as the third dimension in addition to the *x*-*y* coordinates, *H* is related to FD as $FD = 3 - H$. The differences and distances are calculated in directions containing at least four pixels within a circular search region of predefined size (i.e., a ring with inner and outer radii of 4 and 16 pixels, respectively) that moves across the entire

FIG. 1. Examples of x-ray images of (a–c) 5th and (d) 3th distal phalanges with marked bone texture regions (white squares). The images have pixel resolutions and regions ranging from 0.17 to 0.10 mm and from 20 × 20 to 60 × 60 pixels, respectively.

image. The directions are measured with respect to the image horizontal axis.

Previous studies showed that the VOT method can be a valuable tool in early detection and prediction of knee OA.^{20,21} However, its suitability for the analysis of hand OA is not yet known. There are two main reasons for this. The first reason is that hand bones are much smaller than the tibia and femur. Bone texture regions selected on hand radiographs can have a size of 20 × 20 pixels (Fig. 1), which can be almost 13 times smaller than those selected on knee radiographs (e.g., 256 × 256 pixels). We conducted a preliminary study on small images (unpublished results). Fifty 20 × 20 pixel computer generated images of isotropic fractal surfaces with known theoretical fractal dimension $FD_t = 2.1, 2.3, 2.5, 2.7$, and 2.9 (10 images per FD_t) were generated and the VOT method was applied to these images. We found that the FDs calculated by the VOT method do not increase in parallel with the FD_t . Based on this preliminary study we concluded that the search region used in the method is too large for such small images (small number of pairs of pixels separated by large distances), Hurst coefficients are not calculated for the lowest and highest distances and for the directions containing less than four pixels. The second reason is that the longitudinal direction of hand bones is often not perpendicular to the horizontal axis of x-ray images (fingers are oriented in different directions). Consequently, FSs calculated by the VOT method in the horizontal and vertical directions have no interpretation, i.e., the orientation of these two directions with respect to the finger longitudinal direction is not known. Previous studies suggest that analyzing bone texture along these directions is important in the study of OA.^{18,22,23} The problems associated with the size of hand bones and the orientation of fingers are addressed in this paper.

In the present study, first, two new DFS methods are developed for hand bones, i.e., an augmented VOT (AVOT) and a quadrant rotating grid (QRG) methods. Unlike the VOT method, the new methods have the search region adjusted according to the size of TB texture region selected, produce FSs that can be defined with respect to any chosen reference

direction (not necessary the horizontal direction) and use directions with any number of pixels. These were achieved through the development of a new selection algorithm for directions and pixels within the search region, called a recursive multidirectional pixel selection (RMPS) algorithm. Also, in the AVOT method, the size of the two marginal log–log data subsets is reduced from five to three. In the QRG method, Hurst coefficients are calculated at individual scales using an ergodic quadrant estimator instead of the line fittings. The reduction in subsets and the estimator allow for the calculation of Hurst coefficients at lower and higher scales than those used in the VOT method. Second, the accuracy of newly developed methods is evaluated against the VOT method on computer-generated isotropic and anisotropic fractal surface images with known both theoretical FDs and dominating directions. The images had sizes ranging from 20 × 20 to 64 × 64 pixels. The range covers sizes of small regions that can be selected on hand radiographs (Fig. 1). Finally, the ability of the methods to detect OA differences in hand TB textures is tested. For this purpose, TB texture regions were selected on hand radiographs of subjects with (approximate Kellgren-Lawrence (KL) grade ≥ 2) and without (approximate KL grade < 2) radiographic hand OA. The radiographs were obtained from the Osteoarthritis Initiative (OAI) database which is available for public access at <http://www.oai.ucsf.edu>.

2. METHODS AND MATERIALS

Since the VOT method is a base on which the new AVOT method is built, it is described first. Details of the VOT method are given in Ref. 19.

2.A. Texture representation

Texture data is represented as $N_x \times N_y$ pixels digital image, where N_x and N_y are the number of pixels in the horizontal and vertical directions, respectively. Let $L_x = \{1, 2, \dots, N_x\}$, $L_y = \{1, 2, \dots, N_y\}$ and $L_z = \{-1, 0, 1, \dots, N_z\}$ be spatial domains X , Y and gray-scale level domain Z , respectively. $L_z = -1$ denotes an “empty” pixel, i.e., the pixel that is not

FIG. 2. Schematic illustration of (a) the difference $I(\mathbf{x} + \Delta\mathbf{x}) - I(\mathbf{x})$ and the distance $\Delta\mathbf{x}$, and (b) the log-log plot of variances against distances with the line fitted and the Hurst coefficient H .

used in calculations. Then the image can be defined as a function $z_{ij} = I(x_i, y_j)$ which assigns a gray-scale level value $z_{ij} \in L_z$ to a pixel located at $(x_i, y_j) \in L_x \times L_y$, where x_i and y_j are integer numbers representing coordinates of pixels in X and Y domains, $i = 1, 2, \dots, N_x, j = 1, 2, \dots, N_y$, and $N_z = 255$ is the total number of gray-scale level values.

2.B. VOT method

Assuming that $z = I(x, y)$ is generated by a fractal Brownian function, the variance of differences $I(\mathbf{x} + \Delta\mathbf{x}) - I(\Delta)$ can be given by^{24,25}

$$\text{VAR}[|I(\mathbf{x} + \Delta\mathbf{x}) - I(\mathbf{x})|] \propto \Delta\mathbf{x}^{2H}, \quad (1)$$

where $\mathbf{x} = (x, y)$ is the coordinate vector, $\|\Delta\mathbf{x}\|$ is the distance between a pair of points [Fig. 2(a)] and H is the Hurst coefficient. By plotting variances against distances (for all $\mathbf{x}$ and $\Delta\mathbf{x}$) in log-log coordinates and fitting a line to the plot, H can be calculated as a half of the slope of the line fitted [Fig. 2(b)].²⁵ The coefficient is related to the fractal dimension as $\text{FD} = 3 - H$.

The Hurst coefficients can be calculated at different scales and directions. The direction is defined as an angle θ between the line running through a pair of points and the reference line (e.g., the horizontal axis) [Fig. 3(a)]. For each direction, a log-log plot of variances against distances (for $\mathbf{x}$ and $\Delta\mathbf{x}$ along the direction) is constructed and then, divided into overlapping

subsets. A line is fitted to each subset and a set of Hurst coefficients are then calculated at individual scales using slopes of the subset lines fitted. The scale is the distance corresponding to the middle point of the subset [Fig. 3(b)].

The VOT method calculates the Hurst coefficients in the following steps:¹⁹

1. Let $j = 1$.
2. Let $i = 1$.
3. Circular search region L_{xy} with the inner and outer radii of $r_1 = 4$ and $r_2 = 16$ pixels is centred at pixel (x_i, y_j) .
4. Within the search region L_{xy} , absolute differences of gray-scale level values of all pairs of pixels (x_i, y_j) and (x_{nm}, y_{nm}) are calculated, where $n = 1, 2, \dots, N_\theta, m = 1, 2, \dots, N_{dn}$ and N_θ is the number of directions containing at least four pixels and N_{dn} is the number of pixels in the direction θ_n . The differences together with corresponding directions θ_n and Euclidean distances d_{nm} between (x_i, y_j) and (x_{nm}, y_{nm}) are saved in a set R . The direction θ_n is defined as an angle between a line running through the pair of pixels and the image horizontal axis.
5. Number of pixels in directions other than the vertical and horizontal is increased to $N_{d1} = 13$ ($r_2 - r_1 + 1 = 16 - 4 + 1$), i.e., the number of pixels in the horizontal direction θ_1 . This increase is achieved in

FIG. 3. Schematic illustration of (a) the difference $I(\mathbf{x}_\theta + \Delta\mathbf{x}_\theta) - I(\mathbf{x}_\theta)$ and the distance $\Delta\mathbf{x}_\theta$ in direction θ and (b) the log-log plot of variances against distances for θ with the lines fitted to subsets and the Hurst coefficients. Scales are distances associated with the middle points of subsets.

such a way that there are no overlapping pixels between directions.¹⁹ For the new pixels, the absolute differences between gray-scale values along with the distances from (x_i, y_j) are calculated and then added to R .

6. If $i < N_x$ then $i = i + 1$ and go to step 3.
7. If $j < N_y$ then $j = j + 1$ and go to step 2.
8. For each direction θ_n , variances of the differences stored in R are calculated and plotted against the corresponding distances d_{nm} in log-log coordinates. The log-log data points are divided into overlapping subsets of five points shifted by one data point, and a line is fitted to each subset. The distance d_{nm} associated with the middle point of each subset represents an individual scale (i.e., trabecular image size), and the slope β of the line relates to H at this scale as $H = \beta/2$.

2.C. AVOT method

The VOT method has a fixed size search region, calculates FDs in directions defined with respect to the image horizontal axis, does not calculate FDs for directions containing less than four pixels and for scales associated with two lowest and two highest distances. Because of these, the method is not suited for characterization of small bone texture regions and for bone fingers which longitudinal direction is not perpendicular to the image horizontal axis. To overcome these limitations, a special algorithm for the selection of directions and pixels within a search region, called a RMPS algorithm, was developed, and the number of points in the marginal log-log data subsets was reduced from five to three.

The RMPS algorithm selects recursively directions and pixels within a search region in the following steps (Fig. 4):

1. The outer r_2 and inner r_1 radii of a search region are calculated as $\text{floor}(\sqrt{\min(R_w, R_h)})$ and $\text{floor}(r_2/4)$ pixels, respectively, where R_w and R_h are the width and height of a texture region to be analyzed, i.e., the region of interest (ROI). To each direction $N_d = r_2 - r_1 + 1$ pixels are added. The pixels are selected from the search region and details are given in Ref. 19. Let θ_r be a reference direction defined with respect to the image horizontal axis.
2. A set D of directions within a search region is initialised with two coterminal angles, i.e., $D = \{\theta_1, \theta_2\}$ where $\theta_1 = \theta_r$ and $\theta_2 = \theta_r + 2\pi$. Also, a set P of pixels within the region is initialised with N_d pixels belonging to direction θ_1 , i.e., $P = \{P_1\}$.
3. New directions are added to D as follows:
 - a. Define $D' = \{\theta'_n = \theta_n + \frac{\theta_{n+1} - \theta_n}{2} : n = 1, 2, \dots, N_\theta - 1\}$ that takes values between consecutive directions in D . Let $N'_\theta = N_\theta - 1$ be the number of directions in D' .
 - b. Let $n = 1$.
 - c. Generate an empty set P'_n (i.e., a set of pixels belonging to θ'_n) and add N_d pixels to this set as defined in the VOT method. If any of the pix-

FIG. 4. Flow chart of the RMPS algorithm.

els added was used in other direction, then go to step 4.

d. If $n < N'_\theta$ then $n = n + 1$ and go to step c.

e. Add D' to D , set N_θ to the current number of directions in D and then, sort D in such a way that $\theta_1 < \theta_2 < \dots < \theta_{N_\theta}$. Also, add all sets P'_n to P and go to step a.

4. Algorithm finishes and r_1, r_2, N_d, P , and D are stored.

The AVOT method with the selection RMPS algorithm is executed as follows:

1. Let $j = 1$.
2. Let $i = 1$.
3. A search region L_{xy} centred at pixel (x_i, y_j) , a set of directions D , and a set of pixels P are obtained using the RMPS.
4. For each pixel $(x_{nm}, y_{nm}) \in P_n$, where P_n is a set of pixels belonging to θ_n , $P_n \in P$, and each direction $\theta_n \in D$, absolute differences of gray-scale level values of all pairs of pixels (x_i, y_j) and (x_{nm}, y_{nm}) , and the Euclidean distances d_{nm} between the pixels are calculated and then, added to R .
5. If $i < N_x$ then $i = i + 1$ and go to step 3.

6. If $j < N_y$ then $j = j + 1$ and go to step 2.
7. For each direction θ_n , Hurst coefficients are calculated at individual scales as in the VOT method. The exception is that the two marginal subsets of log-log data points contain the first and last three points, respectively, instead of the five points. The reduction in points used allows for the calculation of the Hurst coefficients for small search regions for which the five-point subsets cannot be constructed, e.g., $r_1 = 1$ and $r_2 = 4$ pixels, in the VOT method.

2.D. QRG method

In the VOT and AVOT methods, Hurst coefficients at individual scales are obtained by fitting lines to subsets of log-log plot data points and individual scales are defined as distances associated with the middle points of the subsets. Because of these, the coefficients are not calculated for the lowest and highest distances. In the QRG method, this limitation was overcome by calculating Hurst coefficients using an ergodic quadrant estimator for gray-scale level values selected from the image by means of a rotating grid, i.e.:

1. A set of directions D and values of r_1 , r_2 , and N_d are obtained using the RMPS.
2. Let $n = 1$.
3. A square grid of $N_g \times N_h$ pixels is generated and then superimposed on the image. For $0^\circ \leq \theta_n < 90^\circ$ and $180^\circ \leq \theta_n < 270^\circ$, the N_g and N_h sizes are:²⁶

$$N_g = \text{abs}(\text{floor}(N_x \cos(\theta_n) + N_y \sin(\theta_n))), \quad (2)$$

$$N_h = \text{abs}(\text{floor}(N_x \sin(\theta_n) + N_y \cos(\theta_n))). \quad (3)$$

For other values of θ_n , the negative θ_n (i.e., $-\theta_n$) is used.

4. A matrix $\mathbf{K}$ of size $N_g \times N_h$ is generated and initialised with all values set to -1 .
5. The grid is rotated by an angle θ_n around its center. The grid's x - y coordinates are rounded off to the nearest integer values and the gray-scale level values of the pixels having the rounded off coordinates are copied into $\mathbf{K}$. This process ensures that the original image data are used, not interpolated (i.e., gray-scale values obtained at noninteger coordinates using interpolation). Illustrations and description of the rotating grid algorithm can be found in Ref. 27. For directions other than horizontal and vertical directions, the size of $\mathbf{K}$ is larger than the image size. Thus, some values in $\mathbf{K}$ are -1 .
6. The gray-scale level values are selected from rows of matrix $\mathbf{K}$ at distances $d_m = r_1 + m - 1$ where $m = 1, 2, \dots, N_d$ and are stored into a new set B_{nm} . Since the matrix was obtained by means of the rotating grid, its rows contain gray-scale level values of image pixels located along direction θ_n on the image. This selection is performed as follows:
 - 6.1. Let $m = 1$.
 - A. Let $j = 1$.

- a. Let $i = 1$.
- b. If $\mathbf{K}_{ji} \neq -1$, then value $\mathbf{K}_{ji}$ is added to B_{nm} .
- c. If $i < N_h - d_m$ then $i = i + d_m$ and go to step b.

B. If $j < N_g$ then $j = j + 1$ and go to step a.

6.2 If $m < N_d$ then $m = m + 1$ and go to step A.

7. If $n < N_\theta$ then $n = n + 1$ and go to step 3.

8. Let gray-scale level values in B_{nm} be represented as b_r where $r = 1, 2, \dots, N_r$ and N_r is the total number. Also, let the differences between two consecutive values b_r be represented as b'_r (i.e., $b'_r = b_{r+1} - b_r$). Then, for each set B_{nm} , Hurst coefficients are calculated using the ergodic quadrant estimator.²⁸ This allows calculating Hurst coefficients at lowest and highest distances. Specifically, H is calculated using the following formulas:

$$H = \frac{\log(2\rho + 2)}{2 \log(2)}, \quad (4)$$

where

$$\rho = \frac{\tan\left(\frac{\pi}{2}T\right)}{\sqrt{\tan\left(\frac{\pi}{2}T\right)^2 + 1}}, \quad (5)$$

$$T = \frac{\sum_{r=1}^{N_r-2} \text{sgn}(b'_r) \text{sgn}(b'_{r+1})}{N_r-2}. \quad (6)$$

2.E. Texture parameters

For each scale, the Hurst coefficients obtained are plotted in polar coordinates as a function of direction and ellipses are fitted to the resulting rose plots. Using the ellipses fitted, three texture parameters are calculated at each scale:¹⁹

- Texture minor axis S_{ta} : It measures the dominating roughness component (i.e., $FD = 3 - S_{ta}$) and is defined as half the minor axis length of the ellipse fitted.
- Texture aspect ratio S_{tr} : This is a measure of the surface anisotropy/isotropy and is defined as the ratio of the minor to major axes of the ellipse fitted. For ideal isotropic surfaces (i.e., surfaces exhibiting the same roughness in all directions) S_{tr} is equal to one. For other surfaces, S_{tr} is less than one.
- Texture direction S_{td} : It indicates the dominating surface direction. In the VOT method, this is the angle between the major axis of the ellipse fitted and the reference image horizontal axis. The AVOT and QRG methods can have other directions as the reference.

Sets of S_{ta} , S_{tr} and S_{td} parameters calculated at individual scales are called fractal signature S_{ta} (FS $_{S_{ta}}$), texture aspect ratio signature (StrS) and texture direction signature (StdS), respectively.

2.F. Example application

Examples are provided to illustrate the performance of the VOT, AVOT, and QRG methods in the analysis of three fractal surface images of size 256×256 pixels. The first surface

FIG. 5. Images of (a) isotropic fractal surface with $FD_t = 2.7$ and anisotropic fractal surfaces with the dominating direction of (b) 30° and (c) 120° . (d)–(l) Corresponding rose plots of Hurst coefficients calculated at scales of (d–f) 6, (g–i) 10 and (j–l) 14 pixels using the VOT (asterisk), AVOT (thick line), and QRG (square) methods. Each surface image is 256×256 pixels.

is isotropic and has $FD_t = 2.7$ [Fig. 5(a)]; computer generated using an interpolation method.²⁹ The second and third surfaces are anisotropic and have the dominating direction of 30° and 120° , respectively [Figs. 5(b) and 5(c)]. An inverse Fourier transform method with $FD_t = 2.6$ in 120° and $FD_t = 2.2$ in 30° , and with $FD_t = 2.6$ in 30° and $FD_t = 2.2$ in 120° , was used to generate the surfaces.³⁰

For the AVOT and QRG methods θ_r was set to 0° . The rose plots of Hurst coefficients were obtained and their examples at scales 6, 10, and 14 pixels are shown in Figs. 5(d)–5(l). The shapes of the rose plots indicate correctly the type of sur-

faces analyzed. For the isotropic surface the plots are approximately of a circular shape (almost the same in all directions) [Figs. 5(d), 5(g), and 5(j)]. The rose plots take an elliptical shape with the major axis aligned along the direction of 30° [Figs. 5(e), 5(h), and 5(k)] and 120° [Figs. 5(f), 5(i), and 5(l)] for the anisotropic surfaces. For the isotropic and anisotropic surfaces, the VOT method produced Hurst coefficients at nine scales (from 6 to 14 pixels) in 24 directions. The AVOT and QRG methods produced the coefficients at more scales, i.e., 11 (from 5 to 15 pixels) and 13 (from 4 to 16 pixels), respectively, and in more directions (i.e., 32).

TABLE I. Mean $\pm$ standard deviation of FS_{Sta} , $StrS$ and $StdS$ parameters calculated by the VOT, AVOT, and QRG methods for the isotropic fractal surface with $FD_t = 2.7$ and the anisotropic fractal surfaces with dominating directions of 30° and 120° .

Texture parameter	Method	Isotropic	Anisotropic	
			30°	120°
FS_{Sta}	VOT	2.726 ± 0.038	2.906 ± 0.013	2.922 ± 0.007
	AVOT	2.727 ± 0.045	2.917 ± 0.017	2.923 ± 0.009
	QRG	2.778 ± 0.064	2.916 ± 0.017	2.925 ± 0.015
$StrS$	VOT	0.885 ± 0.059	0.415 ± 0.084	0.317 ± 0.084
	AVOT	0.865 ± 0.068	0.315 ± 0.123	0.285 ± 0.119
	QRG	0.872 ± 0.080	0.411 ± 0.057	0.368 ± 0.074
$StdS$ ($^\circ$)	VOT	113.8 ± 17.8	29.7 ± 4.9	119.4 ± 4.1
	AVOT	105.8 ± 38.7	30.6 ± 4.9	120.2 ± 3.9
	QRG	134.3 ± 40.5	30.4 ± 3.1	119.2 ± 2.3

Texture parameters FS_{Sta} , $StrS$, and $StdS$ were also obtained for the surfaces (Table I). The table shows that the means of FS_{Sta} calculated for the isotropic surface are close to $FD_t = 2.7$. Also, $StrS$ values are about two times lower for the anisotropic surfaces than for the isotropic surface. This indicates that the anisotropic surface exhibits large changes in roughness with direction. The $StdS$ parameter took values around 30° and 120° for the anisotropic surfaces; showing correctly the dominating directions.

2.G. Image databases

For the evaluation of the AVOT and QRG methods, three image databases were constructed. The first two databases contained isotropic and anisotropic computer-generated fractal surfaces of different sizes with known FDs and dominating directions. They were used to evaluate the accuracy in measuring the texture roughness and isotropy/anisotropy. The third database contained TB texture regions of size 20×20 pixels selected on subchondral bone on each side of the 5th distal interphalangeal joint on hand radiographs. Using this database, the ability of the methods to detect differences in TB between hands with and without OA was assessed.

2.G.1. Measurement of surface roughness

Isotropic fractal surfaces with $FD_t = 2.1, \dots, 2.9$ in steps of 0.1 and in four image sizes, i.e., 20×20 , 32×32 , 48×48 , and 64×64 pixels were generated using an interpolation method.²⁹ In total there were 3600 images, i.e., 100 images $\times$ 9 values of FD_t $\times$ 4 image sizes. Examples of the isotropic surfaces which have $FD_t = 2.7$ in four sizes are shown in Figs. 6(a)–6(d).

2.G.2. Measurement of surface isotropy and anisotropy

In addition to the isotropic surfaces, two sets of anisotropic fractal surfaces were used. The first set have $FD_t = 2.6$ in 30° and $FD_t = 2.2$ in 120° . For the second set, the frac-

FIG. 6. Examples of (a–d) the isotropic and (e–l) anisotropic fractal surface images. The isotropic surfaces has $FD_t = 2.7$. The anisotropic surfaces (e–h) have $FD_t = 2.6$ in 30° and $FD_t = 2.2$ in 120° , and (i–l) have $FD_t = 2.6$ in 120° and $FD_t = 2.2$ in 30° . The dominating directions of surfaces (e–h) and (i–l) are 120° and 30° , respectively. The image sizes are in pixels.

tal dimensions were exchanged with the directions, i.e., $FD_t = 2.6$ in 120° and $FD_t = 2.2$ in 30° . The dominating directions of the surfaces in the sets are 120° and 30° , respectively. For each set and image size, 100 surface images were generated using an inverse Fourier transform method.³⁰ This resulted in 800 anisotropic surface images, i.e., 100 images $\times$ 2 sets $\times$ 4 image sizes. Examples of anisotropic surfaces from each set are shown in Figs. 6(e)–6(l).

2.G.3. Detection of differences between OA and non-OA hand TB texture images

A matched case-control study design was used to test the DFS methods in the detection of differences in TB texture between subjects with (cases) and without (controls) hand OA. From each subject a posteroanterior radiograph of one hand was used. On each hand, distal interphalangeal (DIP), proximal interphalangeal (PIP), and interphalangeal (IP), and first carpometacarpal (CMC) joints were graded for joint space narrowing (JSN) and osteophytes on a scale from 0 to 3 points. The grading was performed in accordance with the atlas from OA Research Society International (OARSI)⁴ by a Perth radiologist with over 15 years of experience (Imaging Central, Claremont, Western Australia). A joint was considered as having OA if it exhibited any of the following: (i) JSN grade 2 or worse, (ii) osteophyte grade 2 or worse, or (iii) JSN grade 1 with an osteophyte grade 1. These criteria approximate KL grade 2 or worse.⁷ Pairs of subjects were taken from the first half of the baseline OAI cohort. They were manually and individually matched by sex, age, body mass index (BMI) and race. OAI is a multicenter prospective observational cohort study with the objective of improving public health through the prevention or alleviation of pain and disability from OA. Versions of clinical and image datasets used were 0.2.2 and 0.C.1, respectively. Cases ($n = 20$, gender: 14 women, race: 15 white) were subjects with OA in the 5th DIP

(DIP5) joint. Controls did not have OA. Mean $\pm$ SD values of age and BMI for cases (controls) were 63.0 ± 7.6 (63.0 ± 7.6) and 27.5 ± 4.7 (27.9 ± 4.6), respectively. DIP5 was chosen since this joint is often affected by OA.⁷ The radiographs for cases and controls were selected from those acquired at clinical centre A. This centre has the smallest size hand radiographs (150 DPI, i.e., pixel resolution of 0.17 mm) amongst the five participating centres in the OAI. Other centres have radiographs with 223 DPI (i.e., pixel resolution of 0.11 mm) and more. The small resolution of the images allows evaluating the methods in “the worst scenario,” i.e., small bone regions of 20×20 pixels.

On each hand radiograph, two TB texture ROIs of size of 20×20 pixels were manually selected on subchondral bone on 5th distal and proximal phalanges in the following steps:

1. A square of size 20×20 pixels with a border parallel to the x-ray image horizontal axis is superimposed on the distal phalanx.
2. The square is rotated, if necessary, around its centre so that its top and bottom borders are parallel to the distal joint surface tangent. The angle of rotation with respect to the x-ray image horizontal axis is stored and later used as a reference direction θ_r in the AVOT and QRG methods.
3. Position of the rotated square is shifted horizontally or/and vertically to be located immediately above the cortical plate of the distal phalanx in the centre of the bone epiphysis.
4. A new square, with a border parallel to the x-ray image horizontal axis, of size 29×29 pixels (i.e., $\text{ceil}(20\sqrt{2}) \times \text{ceil}(20\sqrt{2})$ pixels) is superimposed on the x-ray image. This square is called a bounding square. The rotated and bounding squares are concentric.
5. The x-ray image is cropped to the bounding square and pixels with coordinates outside the rotated square are set to -1 .
6. The cropped x-ray image is stored.

For the middle phalanx the ROI selection was similar. The ROIs cover the area of OA bone activities detected in hands using isotope-labelled bone-seeking compounds.⁶ Mean $\pm$ standard deviation of ROIs rotation was $31^\circ \pm 7.5^\circ$. Examples of ROIs located on OA and non-OA hand radiographs are shown in Fig. 7. Each region has a bone area of 3.4×3.4 mm.

2.H. Statistical analysis

The following statistical analysis of texture parameters was performed:

- Shapiro-Wilk tests were used to check normality in texture parameters. $P < 0.01$ was considered significant.
- One-way analysis of variance (ANOVA) with Tukey's Honest Significant Difference (HSD), Games-Howell if appropriate, post hoc tests were performed to compare mean values of texture parameters calculated for surfaces with different FD_t and dominating directions.

FIG. 7. Examples of TB texture ROIs (white squares) located on subchondral bone on each side of (a) OA and (b) non-OA 5th DIP joints. Each ROI is 20×20 pixels.

If necessary, Kruskal-Wallis tests with Mann-Whitney U-test post hoc tests and Bonferroni adjustments were performed in place of the ANOVA. Levene's tests were used to check homogeneity of variances in texture parameters. $P < 0.05$ was considered significant.

- Paired samples t-tests (Wilcoxon signed-rank tests if appropriate) were used to compare values of texture parameters calculated for OA and non-OA TB selected in the 5th distal and middle phalanges. $P < 0.05$ was considered significant.

Analysis was performed using SPSS Statistics 21 (IBM Corporation, Somers, NY).

3. RESULTS

3.A. Measurement of surface roughness

For each FD_t and image size, the mean $\pm$ SDs values of FS_{Sta} were calculated at individual scales, and then, plotted in Fig. 8. The figure shows that at scales 10–14 pixels for 20×20 pixel images the mean values of FS_{Sta} calculated by the VOT method do not increase monotonically with FD_t [Fig. 8(a)] and for 32×32 pixel images there is virtually no difference in FS_{Sta} between images with $FD_t = 2.6$ and 2.7 [Fig. 8(d)]. In contrast, the AVOT and QRG methods had a monotonic increase with FD_t for all image sizes. The AVOT method had the smallest SD values, followed by the QRG and VOT methods. The maximum SDs obtained were 0.149 (VOT), 0.089 (AVOT), and 0.112 (QRG).

For the AVOT method, significant differences ($P < 0.05$) in FS_{Sta} were found between surfaces exhibiting different values of FD_t for all image sizes and at all scales. For the VOT method, there were no significant differences at all scales for 20×20 , at scales 7–14 for 32×32 , and at scale of 12 pixels for 48×48 pixel images. For the QRG method, no differences were found at the two highest scales for images smaller than 48×48 pixels.

FIG. 8. FSS_{sta} calculated for the isotropic fractal surface images of different sizes using the (a, d, g, j) VOT, (b, e, h, k) AVOT, and (c, f, i, l) QRG methods. Markers denote mean values of FSS_{sta} calculated for the fractal surfaces with FD_t = 2.1 (asterisks), 2.2 (square), 2.3 (upward-pointing triangle), 2.4 (circle), 2.5 (diamond), 2.6 (plus), 2.7 (right-pointing triangle), 2.8 (left-pointing triangle), and 2.9 (downward-pointing triangle). 100 images were used per FD_t. The image sizes are in pixels.

3.B. Measurement of surface isotropy and anisotropy

3.B.1. Isotropy

For each FD_t and image size, the mean $\pm$ SD values of StrS were calculated for the isotropic fractal surfaces and then, plotted against the scales (Fig. 9). The means of StrS calculated by the QRG method took values between those calculated by the VOT and AVOT methods. The VOT and QRG methods yielded higher SDs than the AVOT method. The maximum SDs obtained were 0.205 (VOT), 0.147 (AVOT), and 0.181 (QRG). Statistical differences ($P < 0.05$) were found in StrS for all isotropic surfaces, except the VOT method at scales 11–14 pixels for 20×20 pixel images.

3.B.2. Anisotropy

For each set of anisotropic surfaces the mean values of StrS and StdS are shown in Figs. 10 and 11. The mean values of StrS calculated using the VOT method for 20×20 and 32×32 images were lower than those obtained using the AVOT and QRG methods [Figs. 10(a) and 10(d)]. For larger images, all methods produced similar results. Figure 11 shows that for all images the values of StdS calculated using the AVOT method were closer to the known directions (i.e., 30° and 120°) than in the other methods. For 20×20 pixel images at all scales [Fig. 11(a)], and for 32×32 and 48×48 pixel images at scales 8–13 and 11–14 pixels [Figs. 11(d) and 11(g)], the StdS calculated using the VOT method virtually did not change with the dominating directions. For the QRG method, this was observed at only 4 pixel scale and for 20×20 pixel images [Fig. 11(c)]. The maximum SDs obtained for StrS (StdS) were 0.194 (57°) (VOT), 0.184 (38°) (AVOT), and 0.199 (71°) (QRG).

For all image sizes and scales, the AVOT method produces statistically significant differences ($P < 0.05$) in StdS between surfaces with dominating directions of 30° and 120° . Non-significant differences were obtained for the VOT method at all scales for 20×20 , at scales 10 – 13 pixels for 32×32 and at scales 10–14 pixels for 48×48 pixel images. For the QRG method, there was non-significant difference at only 4 pixel scale and for 20×20 pixel images.

3.C. Detection of differences between OA and non-OA TB texture images

FS_{Sta} and StrS were calculated for TB texture ROIs selected on hand radiographs of case and control subjects. Using the AVOT and QRG methods, StdS and FS in the horizontal (FS_H) and vertical (FS_V) directions, i.e., the directions parallel and perpendicular to top and bottom borders of the ROIs, were also calculated. Trabecular image sizes were: 1.02–2.20 in steps of 0.17 (VOT), 0.34 and 0.51 (AVOT), and 0.17–0.68 mm in steps of 0.17 mm (QRG).

Results obtained showed that the AVOT method detects more statistically significant differences (eight differences; $P < 0.044$) in texture parameters between cases and controls as compared to the QRG method (seven differences; $P < 0.049$)

(Table II). For the VOT no statistically significant differences were found.

As compared to controls, the distal phalanx bone texture in cases had lower roughness along the dominating roughness and the horizontal directions (AVOT: FS_{Sta} at 0.34 mm; QRG: FS_H at 0.68 mm) and lower anisotropy (QRG: StrS at 0.17 mm). In the middle phalanx, the lower roughness was also obtained along these two directions [AVOT (QRG): FS_{Sta} at 0.34 (0.17) and 0.51 (0.34) mm; FS_H at 0.34 (0.34) and 0.51 mm]. In the vertical direction, the bone texture roughness was higher [AVOT (QRG): FS_V at 0.51 (0.51) mm]. The anisotropy was lower [AVOT (QRG): StrS at 0.34 (0.34) mm and 0.51] for cases than for controls. For example, using the AVOT method the mean $\pm$ SD values of FS_{Sta} (FS_H , StrS) at size 0.34 mm obtained for control and case subjects in the middle phalanx were 2.691 ± 0.061 (2.670 ± 0.113 , 0.657 ± 0.124) and 2.640 ± 0.062 (2.602 ± 0.090 , 0.758 ± 0.136). For the QRG method, the mean $\pm$ SD values were 2.875 ± 0.041 (2.921 ± 0.172 , 0.443 ± 0.175) and 2.815 ± 0.068 (2.786 ± 0.139 , 0.559 ± 0.152), respectively.

No significant differences were found for StdS parameter.

4. DISCUSSION

In this work, two new DFS methods were developed, i.e., the AVOT and QRG methods, for the analysis of TB texture on hand radiographs. Unlike other methods, they can calculate FSs in many directions for small images (i.e., as small as 20×20 pixel bone regions) with respect to any chosen reference direction (i.e., they work for any orientation of fingers). For these methods, a special algorithm allowing for the adjustment of the search region was developed. Also, the number of points in the marginal log–log data subsets was reduced, and the directions containing less than four pixels and the ergodic quadrant estimator instead of the line fitting were used for the calculation of the Hurst coefficients.

The accuracy of the newly developed methods in measuring texture roughness was evaluated using small images (ranging from 20×20 to 64×64 pixels) of isotropic fractal surfaces with nine known FD_t . The AVOT method produced FS_{Sta} that increased monotonically with FD_t and were statistically significantly different between surfaces with different FD_t for all image sizes and at all scales. For the QRG and VOT methods, FS_{Sta} were not statistically significant at large scales. The reason could be that the methods have less pairs of pixels separated by large distances than those separated by small distances. For example, in case of the VOT method and for 20×20 pixel images, there are four times more pairs of pixels in the horizontal direction separated by 4 pixels than those separated by 16 pixels.

The accuracy of the newly developed methods in measuring surface isotropy and anisotropy was also evaluated. For isotropic surfaces, all methods had values of StrS that were less than 1 and were statistically significantly different between FD_t . This indicates that FDs calculated change with direction. For ideal isotropic surfaces FD is constant in all directions. The change in FD could be explained by the

FIG. 9. StrS calculated for the isotropic fractal surface images of different sizes using the (a, d, g, j) VOT, (b, e, h, k) AVOT, and (c, f, i, l) QRG methods. Markers denote mean values of StrS calculated for the fractal surfaces with $FD_t = 2.1$ (asterisks), 2.2 (square), 2.3 (upward-pointing triangle), 2.4 (circle), 2.5 (diamond), 2.6 (plus), 2.7 (right-pointing triangle), 2.8 (left-pointing triangle), and 2.9 (downward-pointing triangle). 100 images were used per FD_t . The image sizes are in pixels.

fact that computer-generated images are discrete samples of continuous fractals and, consequently, they have FDs varying with directions. We found that StrS values were lower for anisotropic surfaces as compared to isotropic surfaces, except

StrS at scales 11–14 pixels calculated using the VOT method for 20×20 pixel images. For the AVOT method, differences between the isotropic and anisotropic were largest and StdS values calculated were closest to the known dominating

FIG. 10. StrS calculated for the anisotropic fractal surface images of different sizes using the (a, d, g, j) VOT, (b, e, h, k) AVOT, and (c, f, i, l) QRG methods. Markers denote mean values of StrS calculated for the fractal images with dominating directions of 30° (asterisk) and 120° (square). 100 images were used per direction. The image sizes are in pixels.

directions. For the VOT and QRG method, no differences in StrS values were found at some scales between surfaces with different dominating directions. The results indicate that the AVOT method quantifies correctly changes in the surface isotropy/anisotropy.

We tested the ability of the DFS methods to detect differences in TB texture between OA and non-OA hand radiographs. The highest number of statistically significant differences was found using the AVOT method. Specifically, OA TB textures were less rough in the dominating roughness and

FIG. 11. StdS calculated for the anisotropic fractal surface images of different sizes using the (a, d, g, j) VOT, (b, e, h, k) AVOT, and (c, f, i, l) QRG methods. Markers denote mean values of StdS calculated for the fractal images with dominating directions of 30° (asterisk) and 120° (square). 100 images were used per direction. The image sizes are in pixels.

horizontal directions (i.e., lower FS_{Sta} and FS_H , respectively), rougher in the vertical direction (i.e., higher FS_V) and more isotropic (i.e., higher $StrS$) than controls. These differences could reflect on OA changes occurring in bone hands, for

example, such as those found in OA knees, e.g., thickening and realignment of trabeculae.^{20,31} Whether this is the case for hand OA is currently unknown. However, there are ongoing studies aiming to understand the relationships between

TABLE II. Mean $\pm$ standard deviation (P value) of differences of FS_{Sta} , FS_V , FS_H , $StrS$ parameters between cases and controls in the 5th distal and middle phalanges calculated by the AVOT and QRG methods. Statistically significant differences ($P < 0.05$) are in bold font.

Texture parameter	Trabecular image size (mm)	Distal phalanx		Middle phalanx	
		AVOT	QRG	AVOT	QRG
FS_{Sta}	0.17	–	-0.027 ± 0.059 (0.053)	–	-0.023 ± 0.048 (0.049)
	0.34	-0.042 ± 0.088 (0.044)	-0.016 ± 0.012 (0.181)	-0.051 ± 0.089 (0.018)	-0.060 ± 0.080 (0.003)
	0.51	-0.020 ± 0.100 (0.392)	0.002 ± 0.057 (0.868)	-0.048 ± 0.085 (0.021)	0.010 ± 0.062 (0.481)
	0.68	–	0.000 ± 0.077 (0.982)	–	-0.003 ± 0.086 (0.868)
FS_V	0.17	–	-0.007 ± 0.079 (0.686)	–	-0.026 ± 0.093 (0.234)
	0.34	-0.029 ± 0.132 (0.330)	-0.039 ± 0.105 (0.114)	0.020 ± 0.122 (0.481)	-0.005 ± 0.121 (0.852)
	0.51	-0.041 ± 0.156 (0.225)	0.015 ± 0.167 (0.688)	0.076 ± 0.132 (0.019)	0.130 ± 0.163 (0.002)
	0.68	–	-0.009 ± 0.208 (0.846)	–	0.065 ± 0.066 (0.337)
FS_H	0.17	–	-0.025 ± 0.089 (0.231)	–	-0.026 ± 0.076 (0.139)
	0.34	-0.054 ± 0.147 (0.118)	-0.010 ± 0.164 (0.792)	-0.068 ± 0.121 (0.022)	-0.135 ± 0.225 (0.015)
	0.51	-0.028 ± 0.192 (0.521)	-0.032 ± 0.218 (0.514)	-0.101 ± 0.156 (0.010)	0.022 ± 0.201 (0.632)
	0.68	–	-0.114 ± 0.226 (0.037)	–	-0.047 ± 0.226 (0.362)
$StrS$	0.17	–	$+0.52 \pm 0.103$ (0.036)	–	0.001 ± 0.077 (0.934)
	0.34	0.061 ± 0.190 (0.640)	0.056 ± 0.184 (0.193)	0.101 ± 0.169 (0.015)	0.116 ± 0.246 (0.049)
	0.51	0.000 ± 0.260 (0.996)	-0.014 ± 0.232 (0.792)	0.179 ± 0.217 (0.002)	-0.051 ± 0.203 (0.277)
	0.68	–	0.009 ± 0.324 (0.907)	–	0.063 ± 0.282 (0.385)

bone structure and OA in hands. For example, a study using microradiographs showed that OA hand joints exhibit greater zone of calcified cartilage than controls which could lead to vascular canals perforation of cortical plate, and subsequently, to bone ischemia and repair.³² In high-resolution magnetic resonance images (MRIs) of OA hands, subchondral bone sclerosis, bone edema, degradation of collateral ligaments and bone central and marginal erosions were found.^{33,34} Other study showed a positive relationship between hand OA and low bone mineral density.^{35,36}

In our study, the QRG method has the ergodic quadrant estimator. We tested the VOT and AVOT methods with the estimator to check how it affects our results. For the VOT method, values of FS_{Sta} were not statistically different between 20×20 pixel isotropic fractal surface images with increasing FD_r . For the AVOT method, the differences were significant with $P < 0.036$. When the AVOT method was used with its original line-fitting estimator we get $P < 0.001$. Results obtained for the dominating directions and the degree of anisotropy were not satisfactory. Also, we tested the QRG method, but with the line-fitting estimator and non-significant differences were found.

The interpolation method applied in our study produces approximate isotropic fractal surfaces. However, we could generate the exact isotropic surfaces using the Stein method.³⁷ Therefore, we checked whether our results would change when the exact method is used (not shown in this work). We found that values of FS_{Sta} calculated by the AVOT method were statistically significantly different between surfaces with increasing values of FD_l at all scales and for all images sizes. For the VOT and QRG methods, differences were found at some scales and image sizes. For example, for 20×20 pixel images, values of FS_{Sta} were not different at all scales for the VOT method, and at the last two scales for the QRG method. This agrees with the results obtained for the sur-

faces generated using the interpolation method. Unlike for the isotropic surfaces, there is no exact method for the generation of anisotropic surfaces.³⁸

Our results suggest that the AVOT method has the potential to be useful in the analysis of hand radiographs for early OA detection and prediction. The method could be also useful in other applications in medicine and in engineering. In medicine, it could be used in the analysis of rheumatoid arthritis and bone mineral density using hand radiographs,^{14,16} analysis of occlusal forces and detection of osteoporosis using dental radiographs,^{39,40} detection of lung nodules in chest radiographs,⁴¹ or classification of skin lesions on dermoscopic images.⁴² Also, the method could be extended to work on 3D images such as MRI and used, for example, in the characterisation of brain tumors.⁴³ Possible applications in engineering could be found in determination of the condition status of a mechanical system and prediction of machine failure,^{44–46} determination of a relationship between surface texture and coefficient of friction,⁴⁷ and multiscale characterisation of 3D engineering surfaces.⁴⁸

However, there is a limitation in use of our methods. The reference direction θ_r needs to be set manually for each ROI analyzed. This could be addressed through the development of an automated selection of ROIs on hand radiographs. For this, further work is warranted.

5. CONCLUSIONS

The following conclusions can be drawn from this study:

- Two new DFS methods were developed, i.e., the AVOT and QRG methods. Unlike other methods, they use the search region adjusted according to image size, and produce FSs defined with respect to any reference direction. These allow for an analysis of hand radiographs

with small bone texture regions and arbitrarily oriented fingers.

- The newly developed methods were first evaluated using computer-generated images of isotropic and anisotropic fractal surfaces with known FDs and dominating directions. The image sizes were ranging from 20×20 to 64×64 pixels. The AVOT method was the most accurate and reliable in measuring the roughness and isotropy/anisotropy of the surfaces.
- The methods were then evaluated on radiographs of OA and non-OA hands. For this purpose, TB texture ROIs were selected on 5th distal and middle phalanges. The AVOT method was most sensitive to OA changes in the hand radiographs.
- We plan to assess the full potential of the AVOT method in the study of bone texture changes in OA hand initiation and progression by prospective, long-term studies on patient groups at high risk of OA development.

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