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Characterization of Microgravity Effects on Bone Structure and Strength Using Fractal Analysis

Final Report

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1 Abstract

Protecting humans against extreme environmental conditions requires a thorough understanding of the pathophysiological changes resulting from the exposure to those extreme conditions. Knowledge of the degree of medical risk associated with the exposure is of paramount importance in the design of effective prophylactic and therapeutic measures for space exploration. Major health hazards due to musculoskeletal systems include the signs and symptoms of hypercalciuria, lengthy recovery of lost bone tissue after flight, the possibility of irreversible trabecular bone loss, the possible effect of calcification in the soft tissues, and the possible increase in fracture potential. In this research, we characterize the trabecular structure with the aid of fractal analysis. Our research to relate local trabecular structural information to microgravity conditions is an important initial step in understanding the effect of microgravity and countermeasures on bone condition and strength. The proposed research is also closely linked with Osteoporosis and will benefit the general population.

1 Hypothesis/Rationale

- The rationale for this research is based on the premise that microgravity conditions change bone structure in addition to bone mass.
- Bone structure can be characterized by fractal geometry.
- Fractal characterization of bone structural changes due to microgravity conditions is not only optimal but also pragmatic.

2 Specific Aims

The overall goal is the characterization of bone structural changes due to microgravity with the aid of fractals.

- We propose the use of the Alternating Sequential Filters (ASF) method to estimate the fractal dimension of images. When only small window sizes are available, Continuous Alternating Sequential Filters (CASF) will be used for fractal dimension estimation.
- We compute the fractal dimension of subjects participating in the bed rest study.
- We apply fractal analysis to samples of human bone and relate it to mechanical strength.

3 Significance

Protecting humans against extreme environmental conditions requires a thorough understanding of the pathophysiological changes resulting from the exposure to those extreme conditions. Knowledge of the degree of medical risk associated with the exposure is of paramount importance in the design of effective prophylactic and therapeutic measures for space exploration. Major health hazards due to musculoskeletal systems include the signs and symptoms of hypercalciuria, lengthy recovery of lost bone tissue after flight, the possibility of irreversible trabecular bone loss, the possible effect of calcification in the soft tissues, and the possible increase in fracture potential. Our research to relate local trabecular structural information to microgravity conditions is an important initial step in understanding the effect of microgravity and countermeasures on bone condition and strength. The proposed research is also closely linked with Osteoporosis and will benefit the general population.

4 Background

The effect of micro-gravity on the musculoskeletal system is currently being studied. Significant changes in bone and muscle have been shown after long term space flight. Similar changes have been demonstrated due to bed rest. Bone demineralization is particularly profound in weight bearing bones. Much of the current techniques to monitor bone condition use bone mass measurements. However bone mass measurements do not completely describe the mechanisms to distinguish Osteoporotic and Normal subjects.[1] It has been shown that the overlap between normals and osteoporosis is found for all of the bone mass measurement technologies: single and dual photon absorptiometry, quantitative computed tomography and direct measurement of bone area/volume on biopsy as well as radiogrammetry. A similar discordance is noted in the fact that it has not been regularly possible to find the expected correlation between severity of osteoporosis and degree of bone loss .

Structural parameters such as trabecular connectivity have been proposed as features for assessing bone conditions.[1] It has been shown that in vertebral crush fracture patients, elements such as vertical trabeculae are retained more or less intact, while elements such as horizontal bracing trabeculae are resorbed entirely[56] . This results in disconnection of large number of trabecular elements. However, in non-fracture patients connections between elements were preserved. Long vertical trabeculae are subject to buckling under loading. When they lose their lateral connections to adjacent trabeculae, the degree of buckling may exceed the inherent strength of the bone. *Structure can be thus be seen as an important feature in assessing bone condition. In this research, we propose the use of fractals to model the trabecular bone structure.*

5 Fractal Analysis

In the past few years a significant amount of effort has been devoted to the study of chaotic phenomena. A part of this effort is directed towards the study of fractals. As defined by Mandelbrot,[12] fractals are surfaces whose dimensions are strictly greater than their topological dimensions. Intuitively, fractals are surfaces which are embedded in between the m and $m+1$ dimensional manifolds. A fractal object can be characterized by it's dimension which may be interpreted as the quantity of space occupied by the object between the m and $m+1$ dimensional manifolds. Various alternative definitions of dimension have been proposed in the literature. For a detailed discussion of these different definitions the reader is referred to.[141516] This research employs the definition commonly know as the capacity dimension.[15]

It was Kolmogorov[31] who originally proposed the capacity of a set as

$$d = \lim_{\varepsilon \to 0} \frac{\log N(\varepsilon)}{\log(1/\varepsilon)} \tag{1}$$

where if the set in question is a bounded subset of a p-dimensional Euclidean space R^p , then $N(\varepsilon)$ is the minimum number of p-dimensional cubes of side ε needed to cover the set. *For a Fractal set, d can be a non-integer.*

Fractals are known to obey the self-similarity property. Self-similarity implies that the statistical properties of a fractal are independent of the scale or resolution of observation.

There are number of ways in which fractal geometry can be applied to the analysis of image texture. Pentland et al[11] used a method related to the co-occurrence matrix technique of texture classification based on fractal dimension. They found the standard deviations of the difference of gray levels separated by a given vector and plotted it against the vector lengths as a log-log graph. Maragos has used Morphological Covers to estimate Fractal dimension of Synthetic Images.[17] In another technique[7] a two dimensional gray level image is represented as a three-dimensional surface whose height at each point represents the gray level at that point and the surface area is measured at different scales. It has also been shown that[8] an n-dimensional fractal object can be characterized by the fractional Brownian motion of n variables and that the relationship between the power spectral density and r are independent of the projection.[30] This makes the fractal dimension computed from the projections of an n-dimensional fractal object represent the original object. Several studies have modeled radiographic bone images using fractional Brownian motion and have used maximum likelihood estimation to find the fractal dimension.[8,9]

A recent study has indicated that fractal analysis can distinguish between dental radiographs of pre and post menopausal women.[13] Analyses of dental radiographs have been shown to be independent of imaging conditions involved in taking the radiographs (such as the angle between x-ray collimator and anatomical structure of interest) to a significant extent.[10] These preliminary studies also suggest that the fractal measure is to a major extent, independent of the anatomical site being analyzed. Another study used fractal dimensions to attempt predicting osseous changes in ankle fractures.[29]

A variety of methods have been proposed to estimate the fractal dimension of trabecular bone structures.[181922220] *An important problem is the estimation of fractal dimension from images when only small window sizes of the desired structures are available.* In this proposal, a new method based on Alternating Sequential Filters (ASF), is presented to estimate the dimension of a fractal object. When only small window sizes (between 16 x 16 to 64 x 64) are available, we propose the use of Continuous Alternating Sequential Filters (CASF) for fractal dimension estimation. Frequently MRI studies are carried out to provide images of the spine. The individual vetebra occupies only a small region of the entire image of the spine (window size less than 50 X 50). CASF methods are well suited to handle these small window size situations. However, if the window size is greater then 64 x 64, ASF methods can be used.

5.1 Alternating Sequential Filter (ASF)

The method presented here to estimate fractal dimension is based on using Alternating Sequential Filters (ASF). Due to space limitation, a very brief review of ASF is presented. For further details on the morphological concepts presented here the reader is referred to.[4212226] Alternating Sequential Filters appeared initially in the work of Sternberg.[27] The image X is filtered by a closing operation ϕ_1 followed by an opening operation γ_1, then it is filtered again by a larger closing ϕ_2 and a larger opening γ_2, etc..., which in essence produces the operator

$$M_i(X) = \phi_i\gamma_i \dots \phi_1\gamma_1(X) \tag{2}$$

Transformations that apply products of openings and closing in general introduce less distortions than individual operation such as dilations. The operations openings and closing, tend to preserve the 'rough' nature of the image X. Although the use of dilations and erosions have been proposed in the literature to estimate the fractal dimension,[222] it was observed in the scope of this work that ASF's are more suitable for estimating fractal dimension.

Let $\mathfrak{L}$ be a complete lattice. Now define two mappings, a pair of primitives, $(\lambda, X) \rightarrow \gamma_\lambda(X)$ and $(\lambda, X) \rightarrow \gamma_\lambda(X)$ from $\mathbb{R}^+ \times \mathfrak{L}$ into $\mathfrak{L}$ such that for all $\lambda > 0$, γ_λ is an opening and ϕ_λ is a closing such that

$$\lambda \geq \mu \Rightarrow \gamma_\lambda < \gamma_\mu \text{ and } \phi_\lambda > \phi_\mu \tag{3}$$

Note that λ represents the size of the structuring elements used and X is any arbitrary set on $\mathfrak{L}$. Now let m_λ be an operator defined as:

$$m_\lambda = \gamma_\lambda\phi_\lambda \tag{4}$$

and for pairs $\lambda, \lambda' \in \mathbb{R}^+$ with λ' construct the sequence of products

$$\begin{aligned} M_0 &= M_0(\lambda, \lambda') = m_\lambda m_{\lambda'} \,, \\ M_1 &= M_1(\lambda, \lambda') = m_\lambda m_{(\lambda+\lambda')/2} m_{\lambda'} \,, \\ &\vdots \\ M_k &= M_k(\lambda, \lambda') = m_\lambda \dots m_{\lambda+i2^{-k}(\lambda'-\lambda)} \dots m_{\lambda+2^{-k}(\lambda'-\lambda)} m_{\lambda'} \,, 0 \leq i \leq 2^k \end{aligned} \tag{5}$$

A morphological filter called an Alternating Sequential Filter with primitives γ and ϕ and bounds λ and λ' is defined to be:

$$M = M_\lambda^{\lambda'} = \wedge M_k(\lambda, \lambda'), \tag{6}$$

where M is the infimum over all M_k. The mapping M is increasing and idempotent for $\lambda' > \lambda$.

Once an ASF representation of the image is obtained, the fractal dimension can be easily computed with the aid of equation 1.

5.2 Continuous Alternating Sequential Filters (CASF)

We propose the use of CASF when only small window sizes of the desired structure are available in the image. With larger window sizes, ASF methods can be used. The lattice $\mathfrak{L}$ is assumed to be a locally compact Hausdorf topological space. In the digital case the definition of compactness of a space has to be handled more carefully. Let $\mathcal{G}$ be the sampled version of an arbitrary d-dimensional function $\mathcal{F}$, where $m < d$ is the topological dimension of $\mathcal{F}$. It is assumed that $\mathcal{G}$ is the only function available. All characteristics of $\mathcal{F}$ at higher resolutions are lost and as such have to be estimated from $\mathcal{G}$. Compactness of the function $\mathcal{G}$ has to be considered at each scale value at which the function $\mathcal{G}$ is being observed. The following assumptions are made about an arbitrary function $\mathcal{F}$:,

$\mathcal{F}$ is a measurable, continuous, convex and a smooth function with known number of continuous derivatives.

A variety of techniques can be employed to reconstruct the function $\mathcal{F}$ from the function $\mathcal{G}$ given that some of the above assumptions are satisfied.[28]

Let $\mathcal{G}$ be a d-dimensional fractal set. It is noted that d is not necessarily an integer. Also $\mathcal{G}$ is embedded between m and $m+1$ dimensional euclidean manifolds such that $m < d < m+1$. Let $\overline{\mathcal{G}} = \mathrm{ASF}(\mathcal{G})$ be a morphological mapping from $\mathbb{R}^+ \times \mathfrak{L}$ into $\mathfrak{L}$ over some arbitrary neighborhood U defined by the size of the structuring element **B**. Note that the ASF is being used as the locally smoothing operator M described above. The use of ASF filters preserves the global nonlinear characteristics of $\mathcal{G}$ while performing some level of smoothing over the local neighborhood U. Let $\mathcal{G}_\varepsilon = T(\overline{\mathcal{G}})$ be the reconstructed object $\mathcal{G}$ at a resolution scale ε and $\overline{\mathcal{G}}_\varepsilon = \mathrm{ASF}(\mathcal{G}_\varepsilon)$. The sets $\overline{\mathcal{G}}_\varepsilon$ provide a pyramidal representation as different scale values ε are used and the size of $\overline{\mathcal{G}}_\varepsilon$ is changed accordingly. As in (1), let $N(\varepsilon, U)$ be the number of m-dimensional cubes required to cover the neighborhood U of $\overline{\mathcal{G}}_\varepsilon$. Over any arbitrary neighborhood U , the function $N(\varepsilon, U)$ is a mapping from $\mathbb{R}^+ \times \mathfrak{L} \rightarrow \mathbb{R}^+$. The fractal dimension d can then be estimated by:

$$\log \sum_U N(\varepsilon, U) = d \log \varepsilon \tag{7}$$

Note that the sum above is taken over all compact, closed, neighborhoods U of $\overline{\mathcal{G}}_\varepsilon$.

6 Preliminary Experimental Results.

6.1 Bedrest Studies

Fractal analysis was performed on calcaneus regions of subjects undergoing bedrest study. Fig 1 shows one slice of the calcaneus region imaged with the MRI scanner. Figure 2 shows the location of 5 different window locations in which the fractal dimension was computed. Figure 3 shows that the fractal dimension of the calcaneus region as a function of time.

6.2 Fractal Analysis of Tibia

MRI images of an isolated tibia were obtained. Fig 4 shows a slice of the MRI image of the tibia. Fig 5 shows the location of the 53 windows in which the fractal dimension was computed. Fig 6 shows the plot of the fractal dimension as a function for the 53 different window locations in the image.

7 Summary and Conclusions

We have used the fractal dimension to characterize the trabecular bone structure. We have computed the fractal dimension in the calcaneus region of a bedrest subject. We have also computed the fractal dimension of an isolated tibia scanned in the MRI scanner. We plan on relating the fractal dimension to mechanical strength in an ongoing research project.

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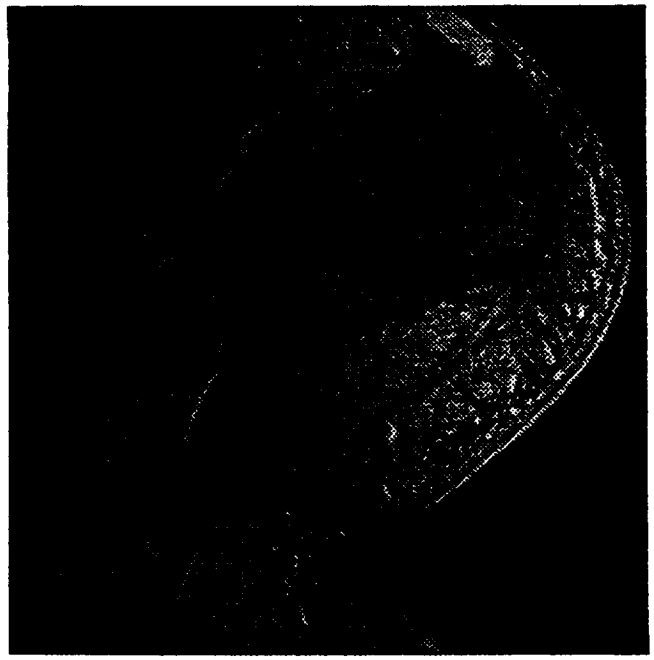


Fig 1

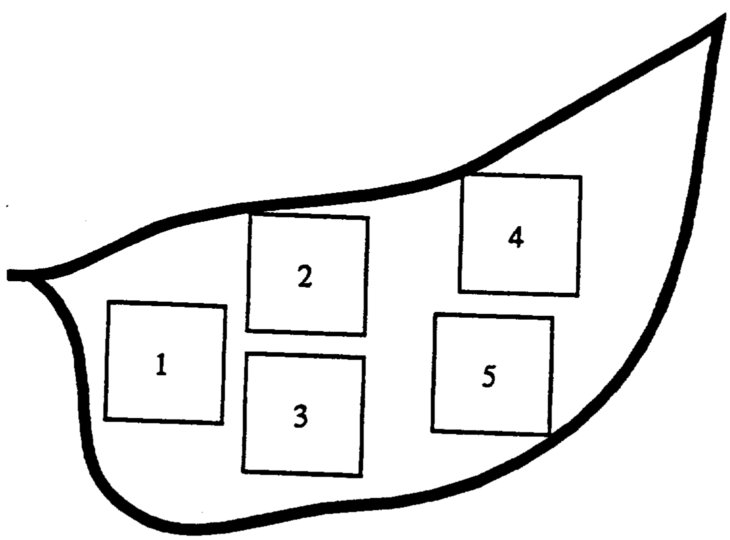
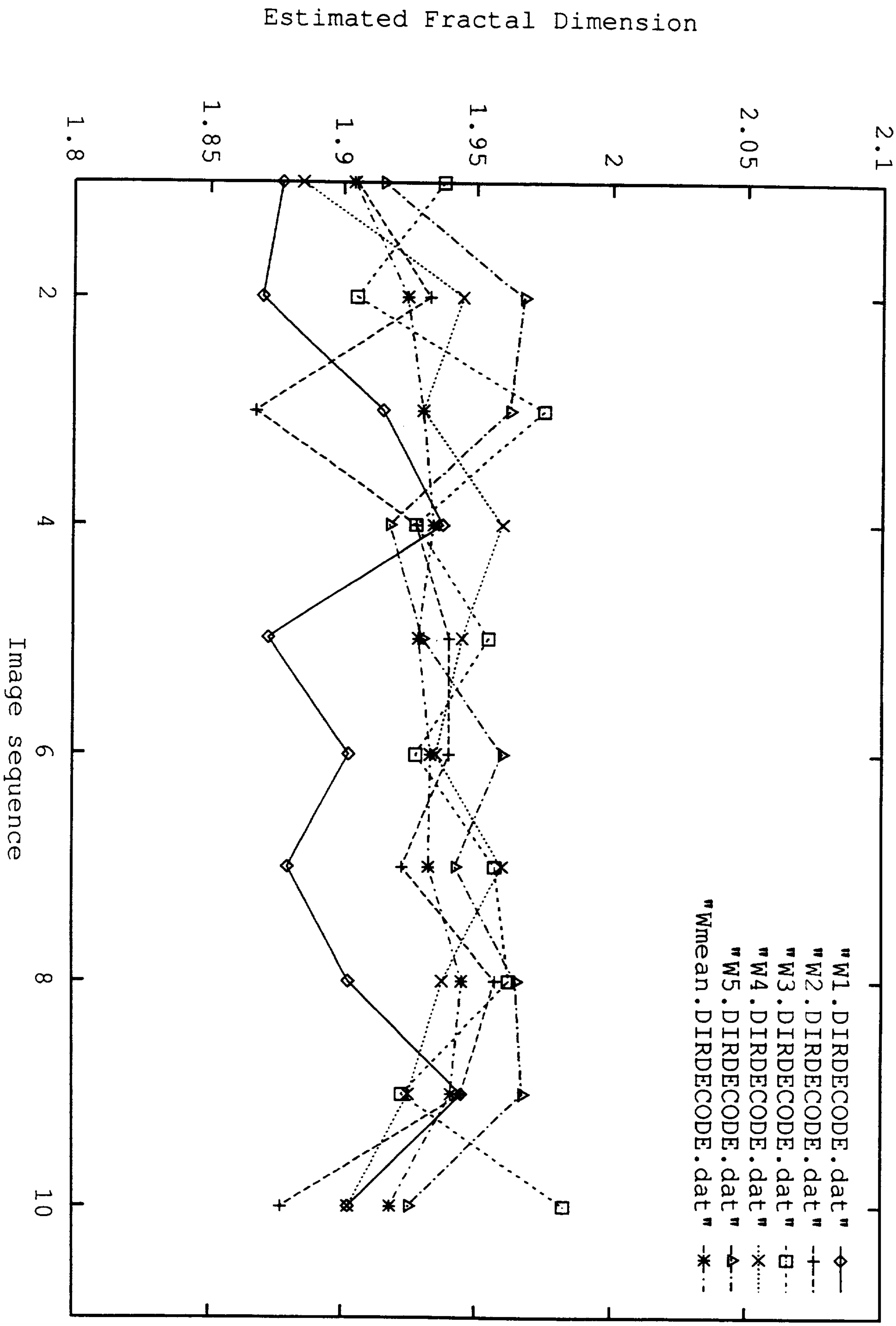


Fig 2



Estimated Fractal Dimension
1.8
1.85
1.9
1.95
2
2.05
2.1
Image sequence
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"W1.DIRDECODE.dat"
"W2.DIRDECODE.dat"
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Fig 3

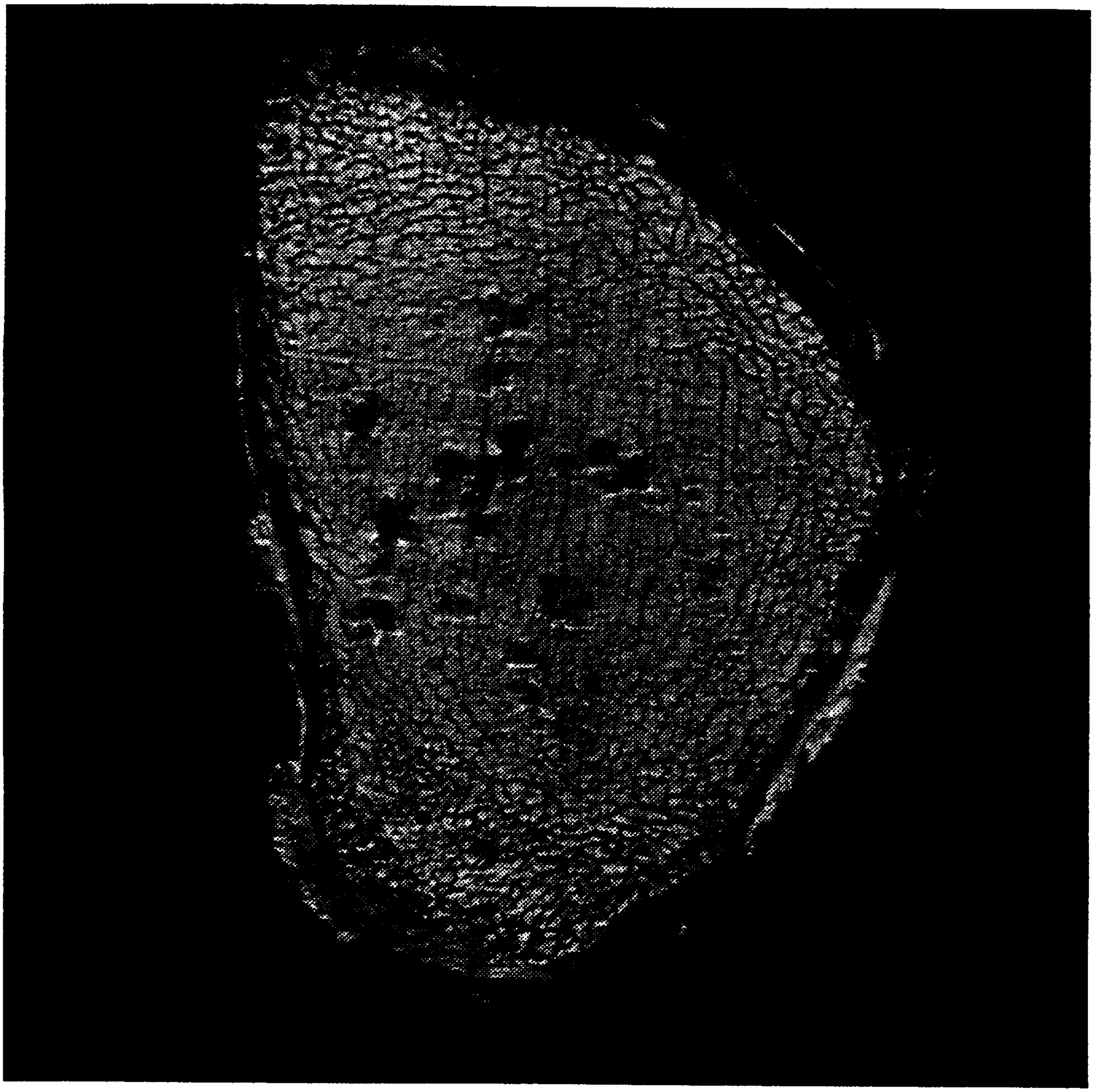

Fig 4

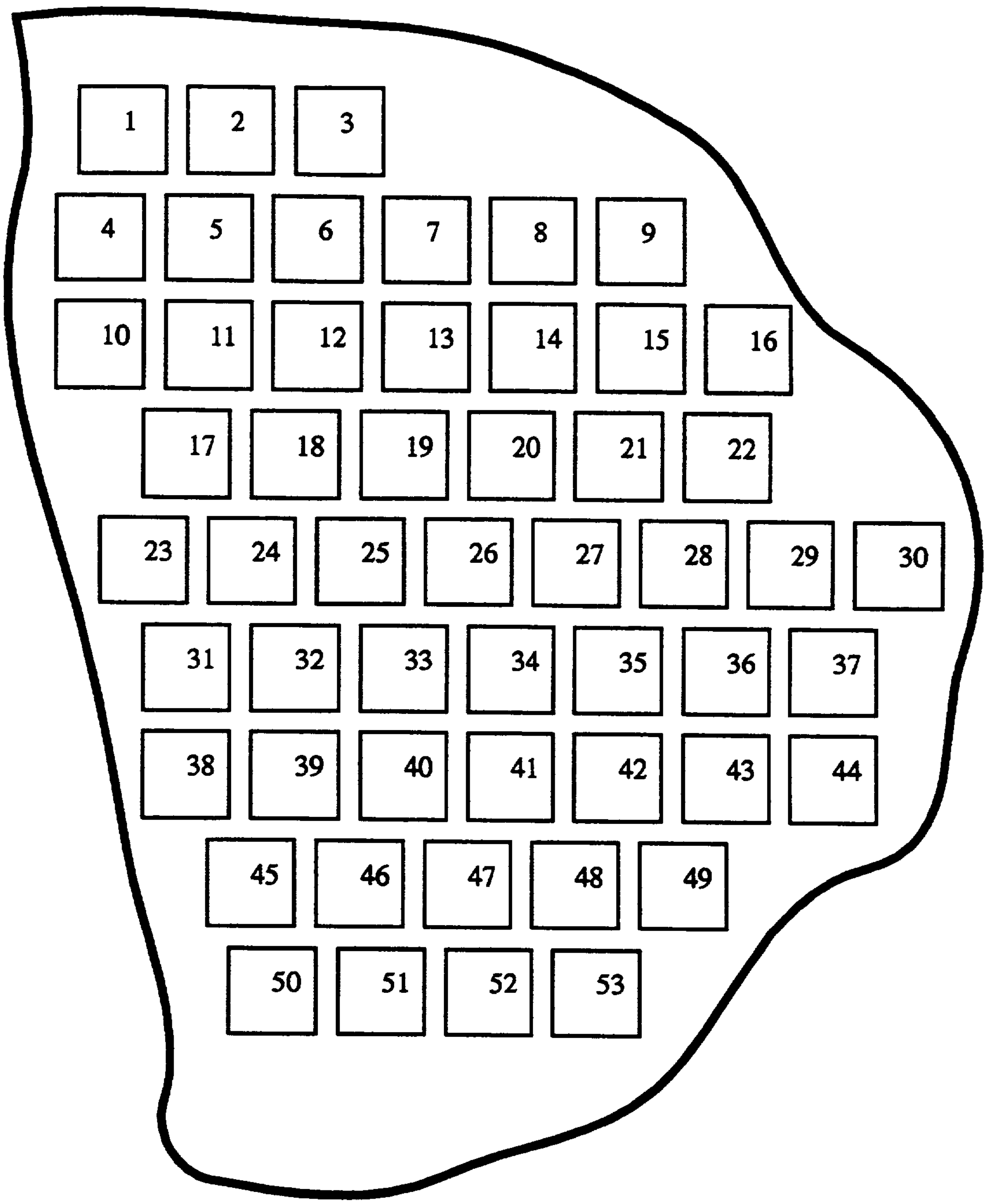
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Fig 5

Estimated Fractal Dimension

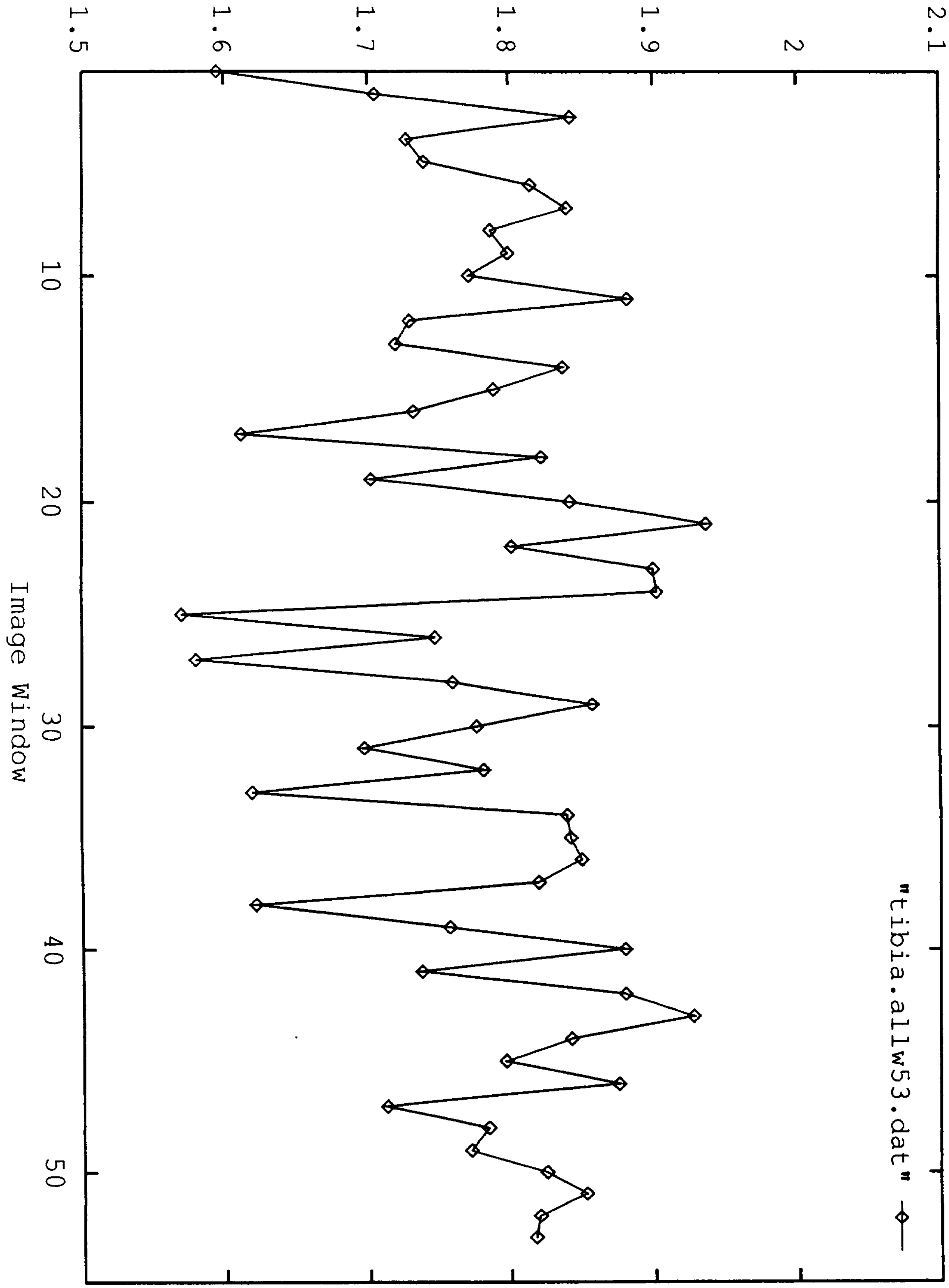

Fig 6