

**Fractal Vasculature and Vascular Network Growth
Modeling in Normal and Tumor Tissue**

by

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B.Sc., Tel-Aviv University (1991)

Submitted to the Harvard-M.I.T. Division of Health Sciences and Technology
in partial fulfillment of the requirements for the degree of

Doctor of Philosophy in Medical Physics

at the

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Abstract

Tumor vascular networks are different from normal vascular networks, but the mechanisms underlying these differences are not known. Understanding these mechanisms may be key to improving the efficacy of the treatment of solid tumors. We studied the scale-invariant behavior of two-dimensional normal and tumor vascular networks grown using a murine dorsal chamber preparation and imaged with an intravital microscopy station. Our studies show that several types of fractal dimensions can quantitatively distinguish different types of vascular networks. We find that vascular networks exhibit three types of fractal behavior. Tumor networks display percolation-like scaling, representing the first evidence for a biological growth process whose key determinants are local substrate properties. Normal networks belong to one of two other classes of fractal structures: normal arteriovenous networks display diffusion-limited scaling, and normal capillary networks are compact (space-filling) structures.

An apparent contradiction arises between the accepted view that angiogenesis is controlled by diffusion and the observation that normal capillary networks are not diffusion-limited structures. A growth model is developed to determine potential mechanisms responsible for the compact shape of normal capillary networks. The model suggests that in normal angiogenesis it is an autocrine mechanism that is key to the formation of a space-filling capillary bed. The growth model is extended to tumor networks by suggesting that substrate inhomogeneity, most likely due the effect of the extracellular matrix in tumor tissue, is responsible for tumor networks' observed fractal properties. The growth model is explored over a range of parameter values.

A growth model is also advanced for the formation of arteriovenous networks. Although arteriovenous networks display diffusion-limited scaling, they are known to form by the remodeling of a pre-existing compact capillary network, where some capillaries get larger while others are resorbed. The growth model shows that a shear stress based remodeling rule for terminal vessels leads to selective resorption of capillaries, transforming a space-filling capillary mesh into a tree-like network.

The percolation-like nature of tumor vasculature is shown to have important transport implications. It may explain why tumor networks have elevated resistance to blood flow compared to normal networks. Furthermore, by elucidating the scaling of avascular spaces and vessel tortuosity, it is shown that percolation-like tumor networks possess inherent architectural obstacles to delivery of diffusible substances to tumor tissue.

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ישמע חכם ויוסף לקח
ונבוז תחבלות יקנה

(משלי א', ה')

(Proverbs 1:5)

Contents

1	Introduction	17
1.1	Motivation	17
1.2	Current State	17
1.3	Long-Term Goal	18
1.4	Hypotheses	18
1.5	Organization	18
2	Background	21
2.1	Angiogenesis	21
2.1.1	Experimental Observations	22
2.1.2	How is Angiogenesis Expressed?	22
2.2	Network Analysis	26
2.2.1	Characterizing Vascular Trees	26
2.2.2	Characterizing Vascular Arcades	27
2.2.3	Fractal Description of Networks	28
2.3	Fractal Growth Processes	30
3	Methods	33
3.1	Dorsal Window Preparation	33
3.2	Image Acquisition	34
3.3	Image Analysis	35
3.4	Fractal Dimension Calculation	35
3.4.1	Box-Counting Algorithm	36
3.4.2	Sandbox Algorithm	36
3.4.3	Correlation Algorithm	37
3.4.4	Algorithm Verification	38
3.4.5	Minimum Path	38
3.5	Statistical Significance Tests	39

3.6	Computer Modeling	39
3.7	Plotting	40
4	Fractal Dimensions of Vascular Networks	41
4.1	Normal Networks	41
4.1.1	Arteriovenous Networks	42
4.1.2	Capillary Networks	42
4.2	Tumor Vascular Networks	42
4.2.1	Tumors of Fixed Size	44
4.2.2	Tumor Networks Over Time	44
4.3	Verification of Fractal Range	45
4.4	Statistical Significance of Results	47
4.4.1	Between and Within-Class Separation	47
4.4.2	Effect of Imaging Method	48
4.5	Discussion	49
4.5.1	Normal Vascular Networks	49
4.5.2	Tumor Vascular Networks	50
5	Modeling Normal Capillary Network Growth	51
5.1	Basic Growth Model	52
5.2	Local Amplification vs. Low Interaction Probability	52
5.3	Model Units and Reality	55
5.4	Model Evaluation	56
6	Modeling Tumor Network Growth	59
6.1	Growth Model Modification	59
6.2	Model Results	59
6.3	Correlation with Biological Observations	60
6.4	Conclusions	61
6.5	Evaluation and Comparison with "Classic" Percolation	62
7	Modeling Arterial and Venous Network Growth	67
7.1	Role of Stress in Vessel Remodeling	68
7.2	Shear-Stress Based Arterialization Model	69
7.3	Model Results	71
7.3.1	Self-Loop Resorption	71
7.3.2	Complex Loop Resorption	72
7.3.3	Resorption on a Lattice	73

7.4	Model Evaluation	75
7.5	Venous Network Formation	76
8	Transport Implications	79
8.1	Geometric Resistance	80
8.2	Scaling of Avascular Regions	81
8.3	Oxygen Transport	82
8.4	Clinical Implications	84
9	Future Directions	87
9.1	Extension to Three Dimensions	87
9.2	Artery and Vein Formation Experiments	89
9.3	Scale-Invariant Networks in Transport Models	90
A	Source Code	93
A.1	External Pascal Routines	93
A.2	Box Counting Algorithm	94
A.3	Sandbox Algorithm	100
A.4	Correlation Algorithm	107
A.5	Minimum-Path Algorithms	114
	A.5.1 Minimum-Path Identification	114
	A.5.2 Minimum-Path Dimension	118
A.6	2-D Growth Modeling Program	126
A.7	3-D Growth Modeling Program	143
A.8	Stress-Based Remodeling Program	163
	A.8.1 Main Routine	163
	A.8.2 Supporting Functions	165
B	Correlation Dimension Measurements	167
C	Fractal Dimensions in Tumor Regression	171
D	In Vitro Verification of Autocrine Mechanism	173
	Bibliography	177

List of Figures

2-1	Mechanisms Involved in Tumor Angiogenesis	25
3-1	Dorsal Window Preparation	34
3-2	Image Analysis Process	36
3-3	Minimum Path in Tumor Vasculature	39
4-1	Fractal Dimensions of Vascular Networks	41
4-2	Skeletonized Images of Vascular Networks	43
4-3	Fractal Dimensions of LS174T Tumor Networks Over Time	45
4-4	Plots for Determination of Fractal Dimension and Range	46
5-1	Effects of Low Interaction Probability and Local Amplification	53
5-2	Growth Time and Efficiency	54
6-1	Effect of Substrate Inhomogeneity	60
6-2	Fractal Dimension as a Function of Model Parameters	62
6-3	Fractal Domains as a Function of Model Parameters	63
6-4	Minimum-Path Dimension as a Function of Model Parameters	64
6-5	Minimum-Path Domains as a Function of Model Parameters	64
7-1	Self-Loop Resorption	71
7-2	Complex Loop Resorption	72
7-3	Loop Resorption on a Square Lattice	73
7-4	Three Generations of Remodeling on a Square Lattice	74
8-1	Fraction of Tissue More Distant in Normal and Tumor Tissue	82
8-2	Oxygenation Contours on a Percolation Network	83
9-1	Fractal Dimensions in 3-D Growth Model	89
B-1	Correlation Dimensions of Vascular Networks	167

C-1	Fractal Dimensions of Shionogi Tumor Networks During Regression	172
D-1	Morphological Archetypes in Endothelial Cell Cultures	174

List of Tables

2.1	Angiogenic Polypeptides and Their Actions	24
3.1	Verification of Fractal Dimension Algorithms	38
4.1	Fractal Dimensions of LS174T Tumor Networks Over Time	44
4.2	Vascular Network Class Separation Based on Fractal Measurements	48
4.3	Effect of Imaging Method on Fractal Dimension	49
B.1	Vascular Network Class Separation Based on Correlation Dimension	168
C.1	Fractal Dimensions of Regressing Shionogi Tumor Networks	172
D.1	Morphological Characteristics of Endothelial Cell Cultures	175

Chapter 1

Introduction

1.1 Motivation

The formation of new blood vessels, or angiogenesis, is a key process in the growth and metastasis of tumors [33]. If a tumor is unable to generate its own blood supply it will not increase in size beyond a diameter of approximately a millimeter. While our understanding of the process of angiogenesis has been greatly enhanced on the molecular level over the last two decades [33], there has been little progress in understanding the angiogenic process on the organ and tissue levels. In particular, it is unclear why tumor vascular networks look so different from normal vascular networks although presumably the same growth factors and inhibitors are involved in their formation. Little is known about the determinants of vascular network formation and architecture — the way in which vessels are arranged and interconnected. This knowledge is important in understanding the differences between physiologic and pathophysiologic angiogenesis, and in designing interventions that modify angiogenesis. Furthermore, this knowledge is essential for characterizing flow and transport in tumor vascular networks so that various therapeutic agents (e.g., drugs, heat, antibodies), which have proved effective *in vitro*, can be better delivered to their target *in vivo* [61, 62].

1.2 Current State

Three major areas of deficiency are noted when trying to study and compare tumor and normal vascular networks:

- To date, there has been no general network description scheme used to study and compare vascular networks. Commonly used schemes [106] are either limited to a particular network topology [29], or to organ-specific [26] or tumor-specific networks [76] and cannot be utilized to describe a wide range of networks.

- While the visual qualitative differences between normal and tumor vascular networks can be readily appreciated, there is little quantitative knowledge about the architectural differences between the two types.
- Currently there is no comprehensive growth model that is able to reproduce the spatial characteristics of tumor and normal vascular networks.

1.3 Long-Term Goal

In view of the above, the goal of this research was to develop a vascular network growth model based on experimental observations, that would facilitate the understanding of the dynamics and determinants of network growth, shape and architecture, and elucidate the characteristics of flow and transport in normal and tumor vascular networks.

1.4 Hypotheses

In order to achieve the long term goal, the following hypotheses were postulated and tested:

1. A general fractal-based non-deterministic network description scheme can quantitatively differentiate normal from tumor vascular networks.
2. Tumor and normal vascular networks correspond to different statistical growth structures based on fractal measurements.
3. The determinants of tumor vascular network architecture are different from those of normal networks.

1.5 Organization

This report is divided into the following chapters:

Chapter 2 provides a thorough background on the relevant facets of the three major disciplines this work encompasses: angiogenesis, network analysis, and fractal analysis. It describes the current state of knowledge and points out the gaps and limitations which this work seeks to overcome.

Chapter 3 discusses the experimental methods used in this research. It includes a description of the animal preparations, the image acquisition and analysis process, the fractal dimension calculation algorithms, and the programming platforms used for modeling.

Chapter 4 describes the fractal dimension measurement results. The statistical significance of the results is calculated, and the implications for growth modeling are discussed.

Chapter 5 is dedicated to the formulation of a normal capillary network growth model. This model helps to identify the key determinants of normal vascular network formation.

Chapter 6 is dedicated to the formulation of a tumor vascular network growth model. This model helps to identify the key determinants of tumor vascular network formation.

Chapter 7 is dedicated to the problem arteriovenous network formation. A vascular resorption model, the missing element in Laplacian arteriovenous growth models, is developed and discussed.

Chapter 8 analyzes the transport implications of the scale-invariant properties of tumor vascular networks. These include elevated geometric resistance in tumors and inadequate delivery of diffusible substances to tumor tissue.

Chapter 9 discusses future directions for extending and applying the research and results discussed in this thesis.

Publications

Some of the results detailed in the following chapters have now been published. The full citations are listed in bibliography References [5, 6, 7, 41, 42, 43, 44, 45, 46].

Chapter 2

Background

This thesis encompasses several traditionally disparate disciplines. In order to permit proper evaluation of this report's contents, some background material will be given in each of these disciplines. First, I will describe the relevant state-of-the-art knowledge in the field of angiogenesis. Second, I will provide a brief review of the traditional methods of vascular network analysis and outline their shortcomings. I will follow with a summary of fractal descriptors that can be potentially applied to vascular networks. Last, I will present a short summary of fractal growth processes. With this background, I hope that the significance of the findings of this research will be clearly understood.

2.1 Angiogenesis

Angiogenesis, the formation of new blood vessels, is essential to reproduction, development, and wound repair. Under normal conditions angiogenesis is highly regulated, activated for short periods and then fully inhibited. There are, however, disease states that are characterized by persistent and unregulated neovascularization. Unregulated angiogenesis occurs most commonly in neoplastic disease, and it is now well-established that tumor growth and metastasis are angiogenesis-dependent. Other disease states that are characterized by unregulated angiogenesis include arthritis, psoriasis, hemangiomas, and approximately 20 ocular diseases. My research focused on tumor angiogenesis.

During the last decade the field of angiogenesis has advanced considerably. At least 25 endogenous molecules stimulating or suppressing angiogenesis have been identified [30]. While much information has been gathered about the biochemical and structural properties of these molecules, there is only a hazy conception regarding the ways these molecules mediate angiogenesis *in vivo* and how they are regulated in both normal and tumor tissue. Furthermore, the interrelations between the different molecules and the interrelations between possible angiogenic pathways are virtually unknown. Since most angiogenesis research has concentrated on the identification of single effector molecules, it is less than surprising that there are only dim ideas regarding the mechanisms which determine the

shape and architecture of a whole network of blood vessels.

In the following paragraphs I will outline some basic experimental observations which are germane to this research, and describe the current biological concepts regarding the expression of the angiogenic phenotype in tumors.

2.1.1 Experimental Observations

Most neovascularization studies [20, 33, 88] have shown that vascular growth occurs on the capillary or post-capillary venule level. One study, dealing with tumor neovascularization in the rat, proposed indirect evidence for angiogenesis on the terminal arteriole level [53]. Generally, however, there is a consensus that only remodeling of existing vessels occurs on the artery-vein level (see Chapter 7).

The dependence of tumors on angiogenesis has been observed in a multitude of experimental models. A tumor's ability to neovascularize is not necessarily connected to its mitotic capability and hence a pre-vascular phase is recognized in tumor development. Lesions at this phase are spherical or flat, grow at a slow linear rate, and rarely metastasize. When neovascularization occurs, the tumor enters a vascular phase which is characterized by rapid exponential growth and increased metastatic potential. The tumor cells prefer to grow around blood vessels, forming cylindrical outshoots into the surrounding tissue. This "preference" is not necessarily connected to the nutrient supply furnished by blood, since this observation has also been made *in vitro* where there was no blood flow in capillaries [100]. The hyperpermeability of the new vessels coupled with the absence of lymphatics lead to an elevation in interstitial fluid pressure (IFP) in tumors. Observed avascular necrotic centers in growing tumors are generally attributed to compression and occlusion of vessels due to growing cancer cells and constantly generated matrix. There are also avascular regions in tumors which never become vascularized, with sizes of up to several hundred microns. It appears that once a threshold number of cells have switched to the angiogenic phenotype, sufficient neovascularization occurs so that the whole tumor population can expand [33]. It should further be mentioned that there are cases in which an angiogenic capability in and by itself is not sufficient for the progression of a solid tumor, since there are benign tumors which are highly vascularized (e.g., adrenal adenomas, hemangiomas).

2.1.2 How is Angiogenesis Expressed?

In the course of investigating the molecular promoters of angiogenesis it became clear that the situation was much more complex than the simple picture of a few molecules secreted by tumor cells which directly influence vascular endothelial cells. There are both inhibiting and activating angiogenic molecules which normally act in concert to maintain a quiescent microvascular network, where the turnover rate of endothelial cells is measured in thousands of days. Even in tumors it has been observed that both proteases and their inhibitors are secreted simultaneously, and that the

balance between them regulates the level of extracellular proteolysis, thus promoting or suppressing angiogenesis. During periods of regulated angiogenesis, as in wound healing, vascular endothelial cells can undergo rapid proliferation, and their turnover is then measured in days, but this process is also rapidly inhibited at the appropriate time. In tumor angiogenesis, the angiogenic phenotype may present in a variety of ways, listed below, that point out to several qualitative classes of processes. Not all of these processes occur in all tumors: some are more common and general, and some occur only in specific tumor types.

Angiogenic molecules effect angiogenesis in various ways:

- Direct mitogenic and/or chemotactic effect on vascular endothelial cells.
- Mitogenic and/or chemotactic effect on other cell types (fibroblasts, macrophages, mast cells) which then produce angiogenic factors.
- Indirect effects on the endothelium (e.g., increase in permeability) and the extracellular matrix (ECM) which initiate a cascade of events leading to angiogenesis.

To complicate the experimental assessment of the effects of these molecules, some molecules may exhibit conflicting effects, depending on the route of administration (e.g., TNF- α is angiogenic when injected extravascularly, but may cause tumor necrosis if injected intravascularly). A list of the eleven best known angiogenic polypeptides and their effects appears in Table 2.1. A diagram adapted from Reference [36] showing a simplified model of angiogenic phenotype expression in tumors is shown in Figure 2-1. The variety and complexity of actions and interactions even in this simple model is evidently great. Nevertheless, several important qualitative features should be noted. First, no matter which molecules are involved, an initial diffusive stage is always present. Second, the diffusing molecules may affect the endothelial cells directly, or by a series of mediators. The possibility of various mediating effects is key to understanding why a simple diffusive model is not sufficient to explain the formation of vascular networks. Third, the complex tumor angiogenesis activation process, as evidenced in Figure 2-1, does not necessarily contain any novel mechanisms which do not occur in normally regulated angiogenesis. Although there are presumably no growth factors which are unique to tumor angiogenesis, it is certain that the processes described in Figure 2-1 can be significantly influenced by changes in the microenvironment of the growing vessels.

As we stand entangled in the myriad of molecular and cellular events involved in angiogenesis and given the large gaps of knowledge even on these levels, it is clear that if one were to take a bottom-to-top approach to unmasking the behavior of vascular networks on the tissue and organ levels, one should expect to spend an extremely long time¹ untangling these mysteries. It is rather simplistic to think that the determinants of vascular network formation can be unlocked by the characterization of one molecule or another.

¹Longer, even, than the time it takes to complete a Ph.D. thesis.

Table 2.1: Angiogenic Polypeptides and Their Actions (after References [33, 35])

Molecule	Effects	Other Properties
aFGF & bFGF	Mitogenic and chemotactic for vascular endothelial cells, fibroblasts, and smooth muscle cells.	Biological activities mediated by heparin or heparin-like molecules. bFGF is sequestered in ECM around blood vessels. Both FGFs are cell-associated and are normally not secreted.
Angiogenin	Does not appear to be mitogenic or chemotactic to vascular endothelial cells.	Present in normal cells and some neoplastic cells. Angiogenin is a secreted protein. Mechanism of angiogenic action not understood.
TGF- α	Mitogenic for vascular endothelial cells, fibroblasts, and epithelial cells.	Secreted by macrophages and some tumors such as sarcomas.
TGF- β	Inhibits growth of many cell types including endothelial cells in vitro, but induces angiogenesis in vivo.	Secreted by many cells in an inactive form. Activated by heat, acid, proteases. Angiogenetic activity may be mediated by macrophages. May have a bifunctional effect on angiogenesis depending on local tissue density of macrophages. Appears to be involved in wound healing, inflammation and differentiation of mesenchymal tissues.
TNF- α	Inhibits endothelial cell proliferation in vitro, but induces angiogenesis in vivo. Chemotactic for endothelial cells.	Secreted by tumor cells as well as by activated macrophages. Thought to be one of the major angiogenic molecules of macrophages.
PD-ECGF	Mitogenic for endothelial cells.	Thought to act physiologically as a maintenance factor for vascular endothelium.
VEGF	Mitogenic for endothelial cells. Increases vascular permeability.	Isolated from various neoplastic cells.
GM-CSF	Endothelial mitogen in vitro.	Granulocyte colony-stimulating factor. Directly augments tumor growth.
PGF	Endothelial mitogen in vitro.	Placental growth factor.
IL-8	Endothelial mitogen in vitro.	Directly augments tumor growth.
HGF	Endothelial mitogen in vitro.	Hepatocyte growth factor.

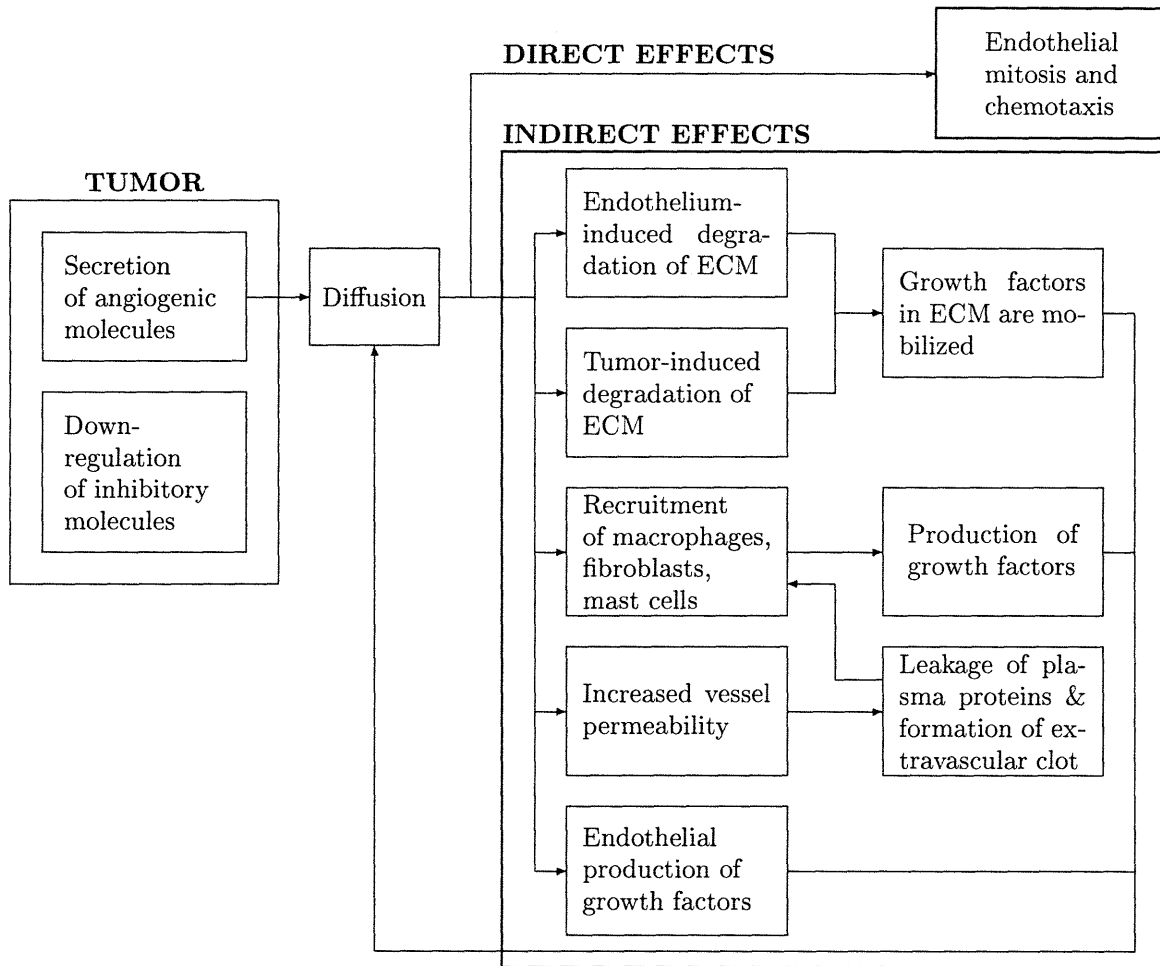


Figure 2-1: Mechanisms Involved in Tumor Angiogenesis

2.2 Network Analysis

Since the question of the determinants of vascular network shape formation cannot be readily answered by considering angiogenesis on the molecular and cellular level, a top-to-bottom approach may prove more practical. Using such an approach, analysis of the properties of the whole network could possibly shed new light on the mechanisms which underlie its formation. This would be beneficial in two ways: in creating a basis for studying the transport properties of vascular networks by facilitating the creation of realistic network models; and in pointing out the key qualitative pathways and cascades in the expression of the angiogenic phenotype. To this end, an overview of “traditional” deterministic network analysis schemes will be given. In delineating their shortcomings, I will lay the ground for the introduction of a non-deterministic (fractal) network analysis scheme.

The most important task in any attempt at network analysis is to develop a description scheme, which functions as the “language” by which the network’s features are described. Such a scheme must be self-consistent so that a unique description is obtained for every network analyzed. Such a scheme should also be generalizable and portable, so that it can be applied to different types of networks. Historically, network description schemes were first developed as a tool in geological research, and were then adopted and expanded by researchers of microcirculation. The researchers were primarily interested in the flow behavior of the systems under study, and thus the descriptors that were developed were not geared towards characterizing the spatial behavior of networks. These descriptors were very useful for designing computer models which reproduced the flow behavior of the experimentally observed networks, but were not concerned with reproducing the spatial behavior of those networks. Only with the advent of fractal geometry did a descriptive tool become available for spatial characterization.

Deterministic network description schemes seek to characterize two major facets of network construction: network topology and network geometry. The topology of the network deals with the way in which vessels are connected to each other, while the geometry of the network deals with the geometric parameters that characterize each vessel in the network (diameter, length, branching angle, taper, cross-sectional shape). The simplest networks to describe are vascular trees. The situation becomes much more difficult if one tries to describe other types of networks. We therefore end up in a situation where network description schemes [106] are either limited to a particular network topology [29], or are limited to organ-specific [26] or tumor-specific networks [76] and cannot be utilized to describe a wide range of networks.

2.2.1 Characterizing Vascular Trees

Two basic methods are used to characterize the vascular topology of trees. The two methods originate from the different ways in which vessel generations can be ordered. The first method to be

employed for microvasculature description classified the vessels according to a centrifugal scheme. The first order was given to the largest vessel in the network, and at each bifurcation the vessels were assigned the same or the next order. This method relied on geometric characteristics of the vessels (diameter, branching angle) to determine the order. In this respect, it is rather arbitrary and impairs the capability to compare the topological characteristics of different networks. Later on, the centripetal method of ordering was applied to vessel networks [29]. In this method, known as the Strahler method, the first order is assigned to the terminal vessels of the network. Subsequently, when two vessels of the same order join together, a next order vessel is formed, and when two vessels of different orders are joined together, the higher order of the two is retained. This method has a major advantage over the centrifugal scheme, since it does not employ any geometric information in classifying the vessels, and therefore the geometric characteristics of the network can be studied independently. Such studies reveal constant branching ratio, diameter ratio and length ratio between different pairs of vessels of consecutive orders [106]. These experimental findings are also known as Horton's laws. Thus, we can define ratios based on the whole network as:

$$R = \frac{1}{K-1} \sum_{k=1}^{K-1} \frac{q_k}{q_{k+1}} \quad (2.1)$$

where K is the highest order in the network, and q is the quantity measured (number of vessels, length, or diameter). The values of these ratios are not independent of each other [67]. The nature of this method allows comparison between different trees, and thus makes it a useful tool for building computer models.

There have been many extensions of the basic features of the ordering schemes outlined above. One such extension [79], for example, used the centrifugal scheme but avoided the reliance on geometric characteristics by incrementing the vessel order automatically at each bifurcation. On one hand, such a method is advantageous for studying the vessels connecting the arteriolar and the venous trees, which are topologically similar in the classic Strahler ordering scheme. On the other hand, it does not elucidate the general geometric properties as the Strahler scheme does.

2.2.2 Characterizing Vascular Arcades

Arcades, or loops, do not lend themselves to such useful general schemes as trees do. In one study of arterial arcades [26], an attempt was made to draw a list of variables that would characterize the arcade, such as the number of feeder arterioles, the number of bifurcations inside or on the perimeter, etc. The independent variables were identified and measurements were made. Although this provided a scheme for quantifying the arcade, there was very little geometric information that could be drawn from such an analysis. Furthermore, it is not a useful scheme for modeling, since it averages out the variances in the data, and it is not generalizable to other types of networks.

There has been an attempt to characterize the complex tumor microvasculature [76] using an adaptation of a centrifugal scheme. The major flaw in such an approach is, again, the reliance on a priori geometric information to characterize the topology, thus inserting a non-negligible arbitrariness into the results, and making them very hard to compare with theoretical models or with other experimental results.

Graph theory provides a convenient way to describe pure topological characteristics of any arrangement of vessels. Although a detailed analysis of vascular topology can be made [132], virtually no geometric or spatial information can be drawn from such an analysis.

Other mathematical representations of vascular networks have been suggested. Such representations [19] inevitably fall into the trap that a generally applicable deterministic method requires so much information about each and every vessel that it cannot be practically applied to the analysis and modeling of large networks.

In summary, this synopsis of the attempts to characterize vessel networks leads to a conclusion that because of the complexity and variability of the structures involved, any method which is based on a vessel-by-vessel analysis is bound to fail. This is especially true when trying to study the erratic architecture of tumor networks. Perhaps the only plausible approach is a non-deterministic analysis of the structure-as-a-whole, which is the topic that will be addressed next.

2.2.3 Fractal Description of Networks

In view of the limitations of the traditional network description schemes, the approach which this research took was a non-deterministic one, where the statistical properties of the network-as-a-whole were described, and vessel-by-vessel analysis was disposed with. Fractal analysis, which relies on the scale-invariant properties of the analyzed objects, offers such an approach (a general introduction to fractals can be found in References [27, 85]). Previous fractal analyses of vascular networks have been mostly limited to measurement of the fractal dimension of the whole network in the natural two-dimensional compartment of the retinal vasculature [28, 72, 82]. As I will next describe, more measurements can be made, from which valuable information and insight can be gained. This is important because different statistical growth processes lead to structures with different fractal dimensions, and by measuring different dimensions one may be able to accurately associate a given structure with a certain statistical growth process (e.g., the fractal dimension d_f of a diffusion-limited aggregate and that of a percolation cluster are the same when both are embedded in three dimensions, but they have a different minimum-path dimension d_{min}).

It should be mentioned that there are various algorithms for measuring fractal dimension. While these algorithms will be discussed in detail in section 3.4, it is important to note that they can yield slightly different results. Measurements of fractal dimension can be applied to carefully defined subsets of the network. The fractal dimensions that can potentially be measured for vascular networks

are:

- The dimension of the network-as-a-whole d_f ; this number characterizes the overall scaling behavior of the structure and gives an idea of how “dense” the network is.
- The dimension of the minimum-path between two opposite sides of the network d_{min} ; this number provides an idea of the efficiency of propagation through the network without revisiting sites [126]. In biological terms it is a measure of the scale-invariant tortuosity of the vessels.

As mentioned above, the benefit of using fractal measurements for characterizing vascular networks does not lie only in the meaningful fractal dimensions that can be measured, but also in the fact that specific values correspond to specific statistical growth processes, which can then be incorporated into growth models. The models’ attributes can then be correlated with the biological processes underlying angiogenesis. A discussion of fractal growth processes follows in section 2.3.

As a final note, there is another benefit to measuring fractal dimensions in view of the traditional methods: Horton’s ratios can be derived from fractal dimension measurements instead of the tedious vessel-by-vessel analysis. To show this derivation, I will use the concept of the diameter exponent Δ that was introduced by Mandelbrot [85]. This diameter (or radius) exponent appears in the equation relating the radii of vessels at a bifurcation:

$$r_0^\Delta = r_1^\Delta + r_2^\Delta \quad (2.2)$$

The diameter exponent is equal to the fractal dimension d_f for self-similar trees [85]. With Equation 2.2 in mind, and with the assumption that at a bifurcation the difference between vessel orders can be 1 at most², it follows that $\sum r_i^\Delta$ is constant for each branching order i and therefore:

$$\sum_{j=1}^{n_i} r_{i,j}^\Delta = \sum_{j=1}^{n_k} r_{k,j}^\Delta \quad (2.3)$$

where k, i are any two branching orders, and n_k, n_i are the numbers of vessels in each order, respectively. Taking into account Horton’s laws one can then write:

$$\sum_{j=1}^{n_i} r_{i,j}^\Delta = R_B^{k-i} \sum_{j=1}^{n_k} \left(\frac{r_{k,j}}{R_D^{k-i}} \right)^\Delta \quad (2.4)$$

where R_B and R_D are the braching ratio and the diameter ratio, respectively.

²In practice, this assumption is only partially valid. Studies of the pig coronary arterial tree [65] and the dog pulmonary venous tree [40] have shown that some bifurcations violate this assumption. It should be noted that these studies used a diameter-dependent vessel ordering scheme and not the classic Strahler scheme which is independent of geometric parameters.

Combining equations 2.3 and 2.4 it follows that:

$$R_B \cdot R_D^{-\Delta} = 1 \quad (2.5)$$

and therefore³:

$$d_f = \frac{\ln R_B}{\ln R_D} \quad (2.6)$$

Other authors have further shown that [110]:

$$\frac{d_f}{d_{min}} = \frac{\ln R_B}{\ln R_L} \quad (2.7)$$

2.3 Fractal Growth Processes

Fractal growth processes reflect non-equilibrium growth phenomena which lead to the formation of scale-invariant structures. While the physical mechanisms that govern the growth may vary from one structure to another, these physical mechanisms can usually be correlated with more general statistical growth rules which group these growth phenomena into four broad classes described below. Generally, each process in each class is defined by a set of statistical growth rules that reflect growth on a square lattice by the addition of identical particles. I will rely on the assumption that if one observes a physical structure whose fractal properties are similar to properties of structures formed by a certain fractal growth process, one can then gain intuition as to the physical mechanisms underlying the growth. With this intuition one can then construct realistic growth models of these structures.

Local Growth Processes

If the statistical growth rule for a particular process depends only on the immediate environment of the site where growth occurs, the growth process is considered local [131]. Examples of such processes are spreading percolation (e.g., as manifested in epidemic spread or flame propagation), invasion percolation (e.g., as manifested by one fluid displacing another in a porous medium). Percolation structures are generally characterized by loops and voids of many length scales and a fractal dimension of $d_f \approx 1.9$ when embedded in two dimensions. To date, no biological growth process has been found to be adequately modeled by a local growth process.

³Equation 2.6 can be verified experimentally for the bronchial tree, which, by virtue of its function, is the only biological tree close to being space-filling. For such a tree we would expect d_f to be close to 3. Indeed, published values for R_B and R_D in the bronchial tree of 4 species [54] concur with our expectation. These values yield a mean d_f of 2.885 in human, 2.831 in dog, 2.809 in rat, and 2.903 in hamster bronchial tree.

Laplacian Growth Processes

Growth processes which are governed by the spatial distribution of a Laplacian field-like quantity (which is inherently non-local) are called Laplacian or “diffusion-limited” [131] (since the probability field of finding a diffusing particle at a given point is a Laplacian quantity). Other such quantities include temperature or electric potential fields. The spatial behavior of these quantities obeys the Laplace equation with moving boundary conditions. Examples of such processes include diffusion-limited aggregation [133] (e.g., as an archetype for bacteria colony formation or viscous fingering), diffusion-limited deposition (e.g., as manifested in electrodeposition), and their many variations. Diffusion-limited aggregation has been found to be a good model for biological growth processes such as neurite growth [18] and bacterial colony growth [10, 87]. Diffusion-limited structures are generally characterized by a tree-like morphology with no loops and a fractal dimension of $d_f \approx 1.7$ when embedded in two dimensions.

Self-Affine and Compact Growth Processes

Not all objects have a non-trivial fractal dimension. There are many growth processes which produce space-filling structures whose dimension is equal to the Euclidean embedding dimension. These structures are known as “compact”. In some of these structures the surface (or interface) is fractal. Irreversible growth processes rarely result in smooth interfaces. If the scaling properties of such an interface are not isotropic it is called “self-affine”. The first model of self-affine interface growth, the Eden model, was actually proposed in conjunction with tumor growth modeling [131]. Other such processes include ballistic aggregation and deposition (e.g., in vapor deposition on a cold substrate). By virtue of its space-filling nature, compact growth implies that there are no variations in local or non-local properties that influence the growth perimeter.

Cluster-Cluster Growth Processes

There are many physical processes where diffusion-limited aggregates (or clusters) are allowed to diffuse themselves. Such processes can be modeled by cluster-cluster aggregation (CCA). CCA well represents the physical mechanisms in an actual system of aggregating particles (e.g., smoke particles), unlike DLA which is more of a general paradigm of Laplacian growth [131]. It is therefore not immediately germane to the problem at hand.

Several qualifying statements should be made regarding the above list:

- There are many variations of these archetypical processes which involve modifications to the growth rules and are too numerous to list. A statistical growth process should be modified

according to the scaling properties of the observed objects, so that it can reproduce these properties.

- While many growth processes are closely related or may display some similar fractal characteristics, there have been extensive studies which have yielded more esoteric exponents that can differentiate among the growth processes [126]. It is then the analyst's task to assign physical meaning to these exponents.
- These archetypical processes are idealizations. They approximate reality only to a limited extent for two reasons:
 - Because of the complexity and variety of physical mechanisms involved.
 - Because of the inherent randomness in the physical mechanisms and the models themselves.

It is useful to think of these statistical growth processes as limiting cases of different physical mechanisms. For example, if one considers flow through a porous medium where both capillary forces and viscous forces are at play, one can see that in the limit where capillary forces are dominant the invasion percolation model holds, and in the limit where viscous forces are dominant the DLA model holds [75]. I will show that vascular networks also display different domains of scale invariant behavior which correspond to different classes of fractal growth processes.

Chapter 3

Methods

This chapter describes the experimental methods used to study vascular networks in this research. It will encompass the procedures implemented in growing the vascular networks, the imaging procedures, and the analysis procedures. The *in vitro* experiments are described separately in Appendix D.

3.1 Dorsal Window Preparation

Two-dimensional vascular networks were generated using the murine dorsal skinfold chamber preparation (Figure 3-1) [73, 78]. The experiments were performed in three mouse strains: C3H, T-cell deficient nude, and severe combined immunodeficient (SCID) mice. The latter two serve as convenient animal models to grow human tumor xenografts without rejection. The mice were bred and maintained in a pathogen-free environment in our laboratory. In an initial surgical procedure, two symmetrical titanium frames (total weight 3.2 g) which are mirror images of each other (Workshop, Department of Radiation Oncology, Massachusetts General Hospital) were implanted in the back of the mouse so as to sandwich the extended double layer of skin. One layer of skin was then micro-surgically removed in a circular area of approximately 15 mm in diameter, and the remaining layer consisting of epidermis, subcutaneous tissue, and thin striated skin muscle was then covered with a coverslip incorporated into one of the frames. Following implantation of the transparent chamber, the animals were allowed to recover for 24 hours [78].

For the study of tumor vascular networks, human colorectal adenocarcinoma LS174T was used in SCID and nude mouse preparations. In addition, three murine tumor cell lines were used in C3H mice: Sa1 murine sarcoma, SCC7 murine squamous cell carcinoma, and MCaIV murine mammary carcinoma¹. The choice of these tumor cell lines was due to previous experience with them in our laboratory and to the existence of published descriptions of their pathophysiologic behavior [1, 78].

¹Near the completion of this study another tumor line, Shionogi (SC115) murine mammary carcinoma, was briefly used in SCID mice. See Appendix C for further details.

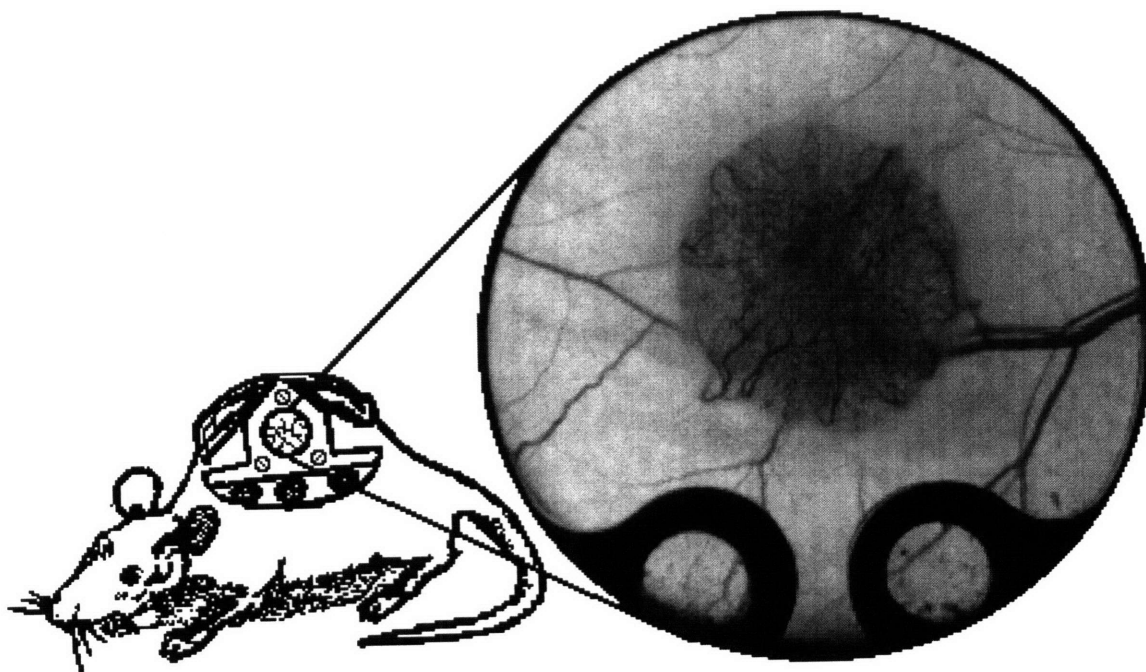


Figure 3-1: Dorsal window preparation in a nude mouse. This chamber was implanted with the LS174T human adenocarcinoma cell line. The tumor is now fully vascularized. The blood in the tumor gives it its dark appearance in relation to the underlying tissue.

The coverslip of the chamber was removed, $2 \mu\text{l}$ of a dense tumor cell suspension from cell culture ($\sim 2 \cdot 10^5$ cells) were inoculated onto the upper tissue layer of the chamber preparation (striated skin muscle), and the coverslip was replaced. The relatively small volume of tumor cells was used so as to avoid disseminated growth of tumors in the whole chamber.

For the study of normal vascular networks two preparations were used. One preparation consisted of the dorsal chamber with no implanted material. This preparation was used to study the normal subcutaneous vascular networks. In a second preparation, bone-implanted nude mice chamber preparations [77] were used. After sacrifice of newborn nude mice, both femora of each animal were bluntly dissected in 10 ml Hanks balanced salt solution (HBSS, Gibco Laboratories, Grand Island, NY) at room temperature and cleaned from soft tissue. Afterwards, femora were transferred to a second dish containing fresh HBSS at room temperature. Only femora without signs of tissue damage (fracture, cartilage damage) as verified under a stereotactic microscope were used for implantation. The coverslip of the chamber was removed, a fresh femur, after 60 minutes of ischemia, was implanted onto the upper tissue layer of the chamber, and the coverslip was replaced [77].

3.2 Image Acquisition

Images of dorsal chamber vascular networks in nude and C3H mice were acquired when the tumors were approximately 4 mm in diameter (7-16 days old). The mice were anesthetized (s.c. injection of

ketamine hydrochloride, 0.1 mg, and xylazine, 0.01 mg, per g body weight) and were then positioned in a polycarbonate tube of 25 mm diameter. The tube was then directed so that the chamber was placed on the stage of an upright microscope (Zeiss Universal; Thornwood, NY) and imaged. Brightfield images were directed to an intensified CCD camera (model 2400; Hamamatsu, Japan). In the intravital microscopy station outside the pathogen-free colony, the video signal was digitized using a PC-AT computer (IBM; Boca Raton, FL) equipped with a DT-2851 image processing board (Data Translation; Marlborough, MA). In the intravital microscopy station inside the pathogen-free colony, the video signal was recorded on a videocassette recorder (model AG-6500; Panasonic; Secaucus, NJ). Images were then digitized using a videocassette player (model SVO-9500MD; Sony, Japan), a time-base corrector (model TBC-IV with ES-2200 expansion system; D.P.S., Florence, KY), and a Macintosh IIfx (Apple Computer; Cupertino, CA) equipped with a DT-2255 image processing board (Data Translation; Marlborough, MA). For contrast enhancement of some normal subcutaneous vascular networks, a bolus of 0.1 ml of fluorescein isothiocyanate-labeled dextran (FITC-dextran, M_r 150000; 5 mg/100 μ l of 0.9% NaCl; Sigma, St. Louis, MO) was injected into the tail vein of the mice approximately 5 minutes prior to image acquisition. Epiillumination was achieved by a 100W mercury lamp (model 770; Opti-Quip, Highland Mills, NY) using an excitation filter (485–505 nm), a dichroic mirror (510 nm) and a barrier filter (530 nm).

3.3 Image Analysis

Image analysis was performed on a Macintosh LC III (Apple Computer; Cupertino, CA) using NIH-Image software (Wayne Rasband, N.I.H.; Bethesda, MD). Raw grayscale images were first processed to maximize contrast. Because the background illumination was markedly uneven, background leveling was achieved by performing grayscale dilation and then smoothing with a Gaussian kernel [111]. The image was subsequently divided into a series of parts. In each part thresholding was performed and the vascular network was traced out. Network tracings were then converted into binary images and skeletonized automatically to prevent artifacts in the subsequent fractal analysis [18]. The image analysis process is summed up in Figure 3-2. Each skeletonized image was verified by projecting it onto the raw grayscale image to assure that no vessels were excluded.

3.4 Fractal Dimension Calculation

The fractal dimension (d_f) of the whole network was measured using three different algorithms. The algorithms were verified against known fractal and whole-dimensional structures (see subsection 3.4.4). The algorithms were implemented using the THINK Pascal programming language (Symantec; Cupertino, CA) on a Macintosh LC III (Apple Computer; Cupertino, CA).

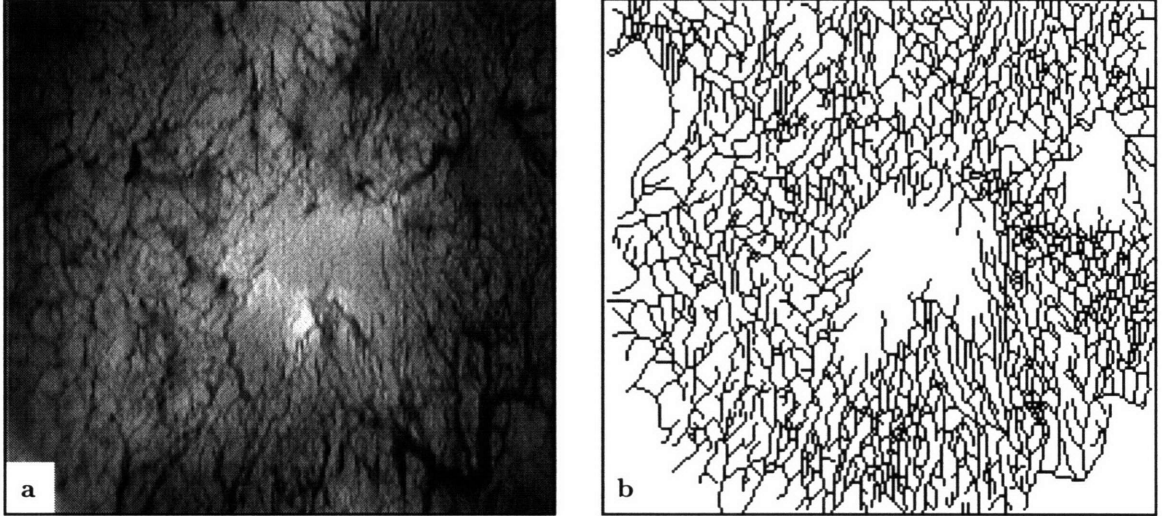


Figure 3-2: The image analysis process: (a) A raw grayscale image of LS174T tumor network in a nude mouse. (b) The subsequent binary skeletonized image. The latter image is the input for the fractal dimension calculation program.

3.4.1 Box-Counting Algorithm

In general, if F is a fractal subset of \mathfrak{R}^n and $N_\delta(F)$ is the smallest number of hypercubes of size δ which can cover F , then the box dimension of F is defined as [27]:

$$d_{box} = \lim_{\delta \rightarrow 0} \frac{\log N_\delta(F)}{-\log \delta} \quad (3.1)$$

In practice this means that if one tiles a fractal object, embedded in two dimensions, with boxes of side ϵ and counts the minimum number of boxes $N(\epsilon)$ occupied by the object, a power law will be observed:

$$N(\epsilon) \propto \epsilon^D \quad (3.2)$$

over the range in which the object is scale-invariant. When a logarithmic plot of $N(\epsilon)$ vs. ϵ is obtained, the fractal dimension is then derived as the absolute value of the slope ($d_{box} = |D|$) of the straight line fit. The implementation of this algorithm iterated over all possible tiling configurations with an ϵ -mesh to find the configuration with minimum boxes. The source code used to implement the box-counting algorithm is listed in section A.2.

3.4.2 Sandbox Algorithm

One can select a pixel i on the fractal, surround it with boxes of increasing side ℓ and count the number of occupied pixels $M_i(\ell)$ in the box. If one repeats this procedure for n different points on

the fractal ($i = 1, \dots, n$), one can obtain the mean number of occupied pixels in a box of side ℓ [14]:

$$M(\ell) = \frac{1}{n} \sum_{i=1}^n M_i(\ell) \quad (3.3)$$

The scale-invariant nature of the object implies that a power law will be observed:

$$M(\ell) \propto \ell^D \quad (3.4)$$

When a logarithmic plot of $M(\ell)$ vs. ℓ is obtained, the fractal dimension is then derived as the slope ($d_{sand} = D$) of the straight line fit. Formally speaking, this algorithm is similar to the box-counting algorithm only if there is no mass-multifractality. Otherwise, it is important to average over many points (Equation 3.3). For a single point, if there is mass-multifractality, then $d_{box} = D_0$ and $d_{sand} = D_{-\infty}$ (the indices 0 & $-\infty$ refer to the order of the generalized dimension [131]). In my implementation of the sandbox algorithm, I averaged over all points on the fractal that were within more than half the maximum box-length ℓ_{max} from the nearest border of the region-of-interest (ROI). The maximum box-length ℓ_{max} is defined as twice the distance from the center of mass to the nearest border of the ROI. This choice of points circumvented artifacts due to boundary effects. The source code used to implement the sandbox algorithm is listed in section A.3.

3.4.3 Correlation Algorithm

The two-point correlation function $c(r)$ of a fractal object of dimension d_f depends on r as [131]:

$$c(r) \sim r^{d_f - d_e} \quad (3.5)$$

where d_e is the Euclidean embedding dimension. Capitalizing on this property, the algorithm chose a pixel i on the object and counted the number of occupied pixels $M_i(r)$ within a spherical shell of radius r and width $0.1r$. The same calculation was repeated for n occupied pixels ($i = 1, \dots, n$) and then normalized by n and by the total number of pixels (occupied and unoccupied) within each spherical shell $N_{pixels}(r \rightarrow 1.1r)$ to estimate the correlation function:

$$c(r) \sim \frac{1}{n \cdot N_{pixels}(r \rightarrow 1.1r)} \sum_{i=1}^n M_i(r) \quad (3.6)$$

Center pixels were chosen according to the same criterion as for the sandbox algorithm to avoid effects due to the boundary region. When a logarithmic plot of $c(r)$ vs. r is obtained the fractal dimension is derived from the slope D of the straight line fit: $d_{corr} = D + 2$. The source code used to implement the correlation algorithm is listed in section A.4.

Table 3.1: Verification of Fractal Dimension Algorithms

Structure	Theoretical Dimension	Box Dimension	Sandbox Dimension	Correlation Dimension
1-D Cantor Set	$\ln 2 \div \ln 3 = 0.63$	0.65 ± 0.02	0.64 ± 0.02	0.58 ± 0.25
2-D Cantor Set	$1 + (\ln 2 \div \ln 3) = 1.63$	1.63 ± 0.03	1.63 ± 0.02	1.63 ± 0.05
Koch Curve	$\ln 4 \div \ln 3 = 1.26$	1.28 ± 0.01	1.27 ± 0.00	1.24 ± 0.03
Sierpinski Gasket	$\ln 3 \div \ln 2 = 1.58$	1.60 ± 0.00	1.59 ± 0.00	1.56 ± 0.02
Sierpinski Carpet	$\ln 8 \div \ln 3 = 1.89$	1.87 ± 0.01	1.88 ± 0.00	1.87 ± 0.01
Straight Line	1.00	1.00 ± 0.00	1.00 ± 0.00	0.93 ± 0.08
Circle – Frame	1.00	1.01 ± 0.00	1.00 ± 0.00	1.01 ± 0.02
Circle – Filled	2.00	1.98 ± 0.00	2.00 ± 0.00	2.00 ± 0.00
Square – Frame	1.00	1.01 ± 0.00	1.02 ± 0.00	0.95 ± 0.04
Square – Filled	2.00	2.00 ± 0.00	2.00 ± 0.00	2.00 ± 0.00

3.4.4 Algorithm Verification

In order to verify that the source code implementing the three algorithms above is free of bugs, the algorithms were tested on a variety of fractal and whole-dimensional structures. The results of these tests are presented in Table 3.1. The results show that the box-counting and sandbox algorithms, as implemented in the source code listed in sections A.2 and A.3, are accurate and robust. The correlation algorithm, as implemented in the source code listed in section A.4 is less accurate than the other two in most of the cases.

3.4.5 Minimum Path

In addition to measuring the fractal dimension of the whole network, the fractal dimension of the minimum path d_{min} between two opposite sides of the network [126] was measured. In order to find the minimum path, all the points on one edge of the ROI were first marked and assigned a value of 1. Their nearest neighbors were then identified, and assigned a value of 2. The procedure continued in a similar fashion, marking the nearest neighbors in each subsequent iteration with an integer value incremented by 1. Once a value was assigned to a point, it could not be reassigned. The iterations continued until a point of the opposite edge of the ROI was reached. Then the program worked backwards from that point to find points with decreasing value, thus marking the minimum path. An example of a minimum path can be seen in Figure 3-3. The fractal dimension of this minimum path was measured by a modified box-counting algorithm. The “boxes” were rendered as straight lines, whose origin and end must fall on the minimum path. In this respect, the fractal dimension measurements were similar to the Richardson method used to measure coastlines [84]. In order to assure the accuracy of the results, the algorithm iterated over all possible configuration for covering the minimum path. The configuration utilizing the minimum number of lines was then chosen for the calculation. The calculation was performed as described in subsection 3.4.1. The source code used to identify the minimum path and calculate its fractal dimension is listed in section A.5.

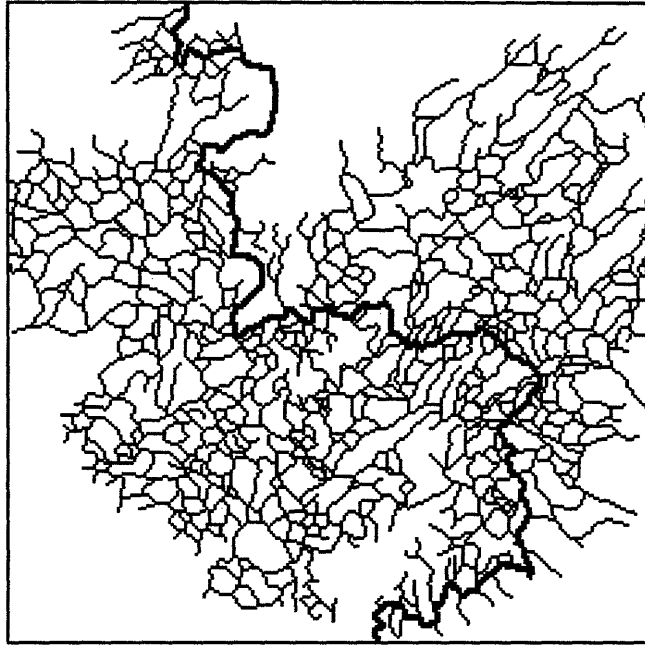


Figure 3-3: An example of the minimum path in tumor vasculature. The vascular network shown is from SCC7 tumor implanted in C3H mouse. The minimum path appears in bold. The fractal dimension of this minimum path is 1.16 ± 0.01 .

3.5 Statistical Significance Tests

In cases where the statistical significance of the difference between two unpaired groups of observations needed to be measured, two different unpaired comparison tests were used:

- The unpaired t-test, which compares the means of two groups and determines the likelihood of the observed difference occurring by chance, under the hypothesis that the means of the two groups are equal. This likelihood is reported as a p -value. This test assumes that the observations in each group are normally distributed.
- The Mann-Whitney U-test, which is the nonparametric version of the unpaired t-test. The Mann-Whitney U-test does not make any assumptions about the underlying distribution of the observations in the two groups. It tests the hypothesis that the distributions underlying the two groups are the same. The result is also reported as p -value.

3.6 Computer Modeling

Computer modeling of tumor and normal capillary growth was performed using two different platforms. Initial modeling efforts were carried out using the THINK Pascal programming language (Symantec; Cupertino, CA) on a Macintosh LC III (Apple Computer; Cupertino, CA). This programming environment offered a user-friendly interface which provided instant visual feedback about

the model results, albeit at the expense of computing time. Once the model was verified to be bug-free (to a satisfactory degree of certainty), it was reprogrammed using the FORTRAN 77 programming language on a much faster UNIX platform.

The random number generator used in the modeling was of the congruential multiplicative type:

$$x_i \equiv cx_{i-1} \pmod{(2^{31} - 1)} \quad (3.7)$$

with a multiplier $c = 950706375$ and with shuffling. This specific generator stood up to extensive empirical tests [32]. It was employed via the FORTRAN routine package IMSL STAT/LIBRARY (IMSL; Houston, TX).

Computer modeling of arteriovenous network growth was performed using the MATLAB (MathWorks; Natick, MA) matrix manipulation software on various UNIX platforms provided by MIT's Project Athena.

3.7 Plotting

The plots in this document were generated using the public domain plotting package Gnuplot. The interpolations were generated with the MATLAB package using a cubic smoothing spline. The smoothing parameter s_p was in the range $[0.999, 1]$. For $s_p = 0$, one obtains the least-squares straight line fit. On the other extreme, for $s_p = 1$, one obtains the "natural" cubic spline interpolant.

Chapter 4

Fractal Dimensions of Vascular Networks

Fractal dimensions were measured in a variety of normal and tumor vascular networks grown in the two-dimensional murine dorsal chamber preparation described in section 3.1. Results of these measurements (using the box-counting and sandbox algorithms) are summarized in Figure 4-1. A skeletonized image typical of each class of vascular networks discussed below is shown in Figure 4-2. Results of measurements using the correlation algorithm are listed separately in Appendix B, since benchmark tests showed that this algorithm is less accurate than either the box-counting or sandbox algorithms (see subsection 3.4.4).

4.1 Normal Networks

Normal networks can be broadly divided into two categories: arteriovenous networks and capillary networks. Arteries and veins are different from capillaries in several ways. Histologically, arteries and

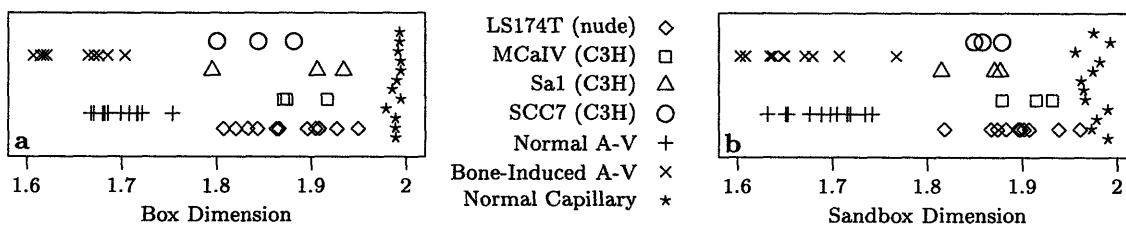


Figure 4-1: Fractal dimensions of the observed vascular networks. (a) As measured with the box-counting algorithm. (b) As measured with the sandbox algorithm.

veins contain smooth muscle cells and an adventitial layer, whereas capillaries do not [63]. Geometrically, arteries and veins are of consistently larger diameter than capillaries. Topologically, arteries and veins usually form a tree-like structure, whereas capillaries form a mesh-like structure [106]. The dorsal window provides a convenient preparation in which the arteriovenous and capillary networks can be easily differentiated since the arteriovenous network resides in a focal plane different from the striated skin muscle capillary network connected to it.

4.1.1 Arteriovenous Networks

Measurements of normal subcutaneous arteriovenous networks yielded values of $d_{box} = 1.70 \pm 0.03$ and $d_{sand} = 1.70 \pm 0.03$ in nude mice ($n = 12$); and $d_{box} = 1.72 \pm 0.02$ and $d_{sand} = 1.71 \pm 0.03$ in SCID mice ($n = 23$). The minimum-path dimension measured was $d_{min} = 0.99 \pm 0.02$ in nude mice and $d_{min} = 1.00 \pm 0.01$ in SCID mice. The normal subcutaneous arteriovenous networks were quiescent and were not growing at the time of measurement. In order to verify these results in a growing normal vascular network, the fractal dimension in bone-induced arteriovenous networks [77] was measured. In this preparation, the networks grew on a topologically two-dimensional surface (the bone surface). However, since this surface is not two-dimensional in the Euclidean sense, the field of view in which the network was in focus was more limited than in the standard dorsal window. Measurements of bone-induced arteriovenous networks ($n = 10$) yielded $d_{box} = 1.65 \pm 0.04$ and $d_{sand} = 1.66 \pm 0.05$. The minimum-path dimension was $d_{min} = 1.00 \pm 0.01$.

4.1.2 Capillary Networks

All capillary networks were imaged with the aid of a fluorescent contrast material (see section 3.2), since the relatively low number of red blood cells in each of these thin vessels could not provide enough contrast. Only intact quiescent networks where the vessels were not leaky could be imaged with this method. Measurements of normal striated skin muscle capillary networks in nude mice ($n = 12$) yielded $d_{box} = 1.99 \pm 0.00$ and $d_{sand} = 1.97 \pm 0.01$. The minimum-path dimension was $d_{min} = 1.00 \pm 0.02$.

4.2 Tumor Vascular Networks

The vascularization of tumors is a dynamic process. In the first stages of vascularization, the new vessels are not fully formed. This condition produces microhemorrhages in the tumor, which make the observation of the new vasculature virtually impossible [78]. In addition, the rate of vascularization may vary significantly between tumors. Taking into account that tumor size in the vascular phase of tumor growth is directly dependent on the level of vascularization, it was decided to study tumors of comparable sizes (approximately 4 mm in diameter). Tumors from the same cell line

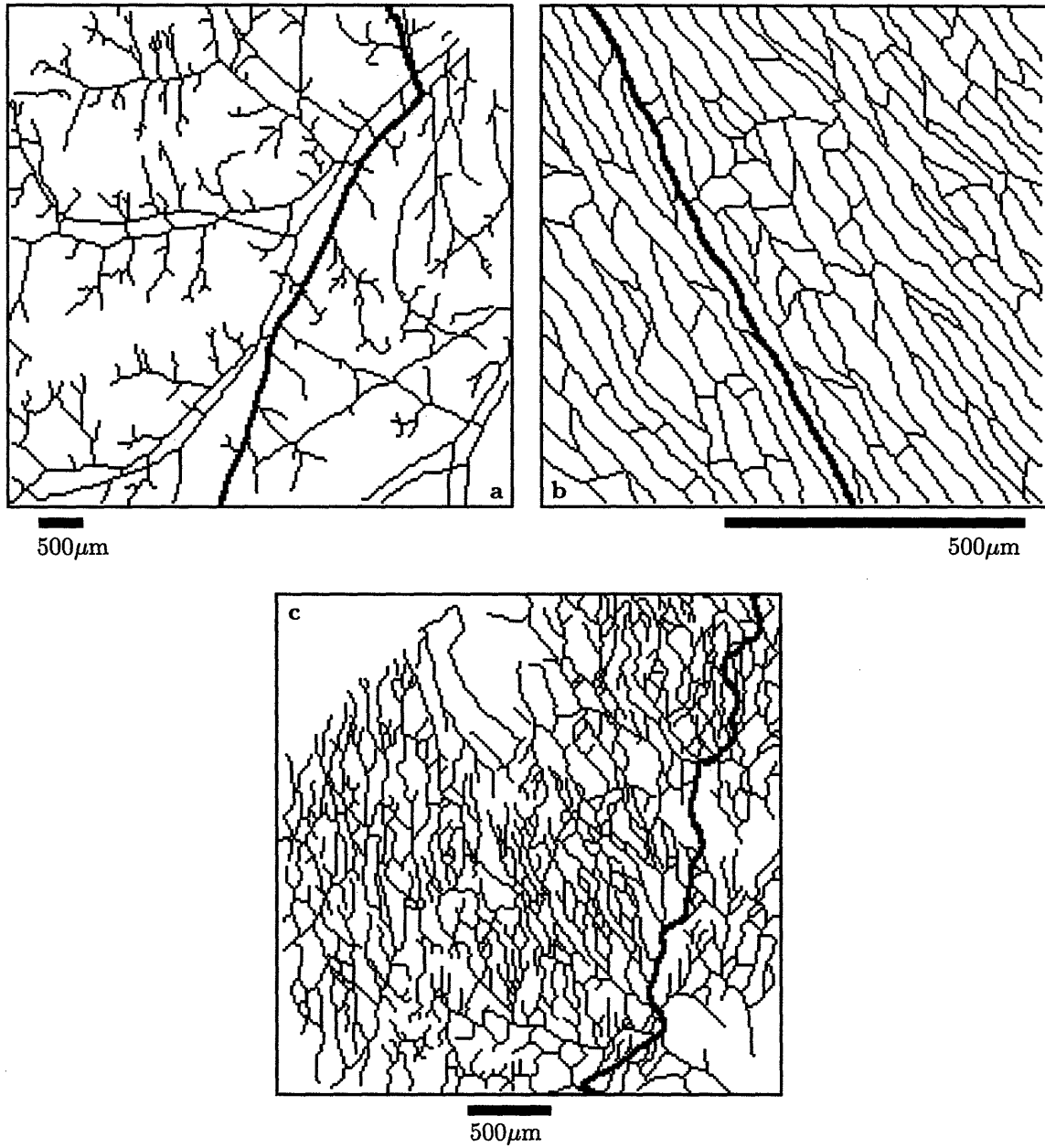


Figure 4-2: Typical skeletonized images of the three observed classes of vascular networks. (a) Normal subcutaneous arteriovenous network in a SCID mouse; (b) Normal subcutaneous capillary network in a nude mouse; (c) LS174T tumor network in a nude mouse. The minimum path is in bold.

Table 4.1: Fractal Dimensions of LS174T Tumor Networks Over Time

Dimension	day 10	day 14	day 18	day 22
Box-Counting	1.69 ± 0.07	1.81 ± 0.05	1.83 ± 0.02	1.84 ± 0.04
Sandbox	1.72 ± 0.06	1.84 ± 0.03	1.85 ± 0.02	1.85 ± 0.03
Minimum Path	1.10 ± 0.03	1.08 ± 0.02	1.09 ± 0.02	1.09 ± 0.03

reached this size in approximately the same time¹. In a separate study, one type of tumor (LS174T implanted in SCID mice) was followed for a period of 12 days, measuring the fractal dimensions every 4 days. The duration of the experiment was limited by the viability of the dorsal chamber.

In tumors, unlike normal tissue, arteries, veins and capillaries cannot be distinctly classified [60]. The vessels' geometric parameters can vary dramatically, regardless of topological parameters or histological characteristics [68]. Therefore, in tumors the fractal dimension was measured for all observed vessels taken together.

4.2.1 Tumors of Fixed Size

Measurements of human adenocarcinoma LS174T vascular networks ($n = 12$) in nude mice yielded $d_{box} = 1.88 \pm 0.04$ and $d_{sand} = 1.89 \pm 0.04$. The minimum-path dimension was $d_{min} = 1.10 \pm 0.04$. To test the generalizability of these results, fractal dimensions were measured in C3H mice implanted with three different murine tumor cell lines ($n = 3$ for each). The results of these measurements are summarized in Figure 4-1. One can see that the additional results are consistent with the results for the LS174T tumor networks.

4.2.2 Tumor Networks Over Time

Fractal dimension measurements of human adenocarcinoma LS174T vascular networks ($n = 7$) were performed on images acquired on days 10, 14, 18 and 22 after tumor cell inoculation (only on day 10 does the optical quality of the tumor become sufficient for these measurements). The measurements are summarized in Table 4.1 and presented graphically in Figure 4-3.

These results show that approximately on day 14 after inoculation the fractal dimension of the whole network reaches a “steady-state” value. The reason for the initial period of rising fractal dimension lies in the fact the the inoculated tumor cell mass lacks any vessels, so only around day 14 does the tumor become “fully” vascularized (afterwards vascularization follows tumor growth). This explanation is consistent with the observation that tumor vascular density in the same animals also reached a “steady-state” value at approximately day 14 [78]. The mean fractal dimension values in Table 4.1 are slightly lower than the mean values reported in LS174T tumor networks in nude mice (see subsection 4.2.1). This is most likely due to the lower quality of images acquired using the

¹Even if the tissue environment was exactly the same in all mice, there would be inevitable variations due to the inaccuracy in measuring the initial amount of tumor cell inoculate.

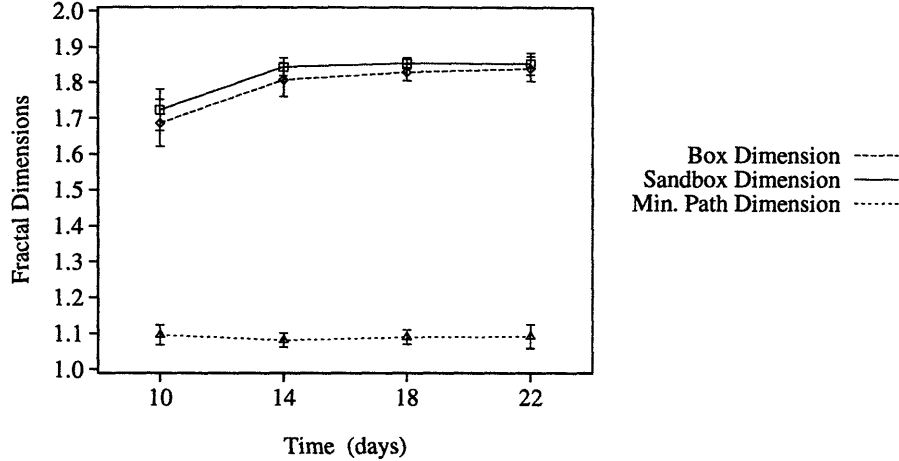


Figure 4-3: Fractal dimensions of LS174T tumor networks over time. Each point represents the mean and standard deviation of measurements in 7 different animals.

analog image acquisition system necessary for following the same animal over time (see section 3.2).

The minimum-path dimension, however, remained statistically unchanged during the whole measurement period, and it was nearly identical to the minimum path dimension measured in tumor networks in nude mice (see subsection 4.2.1). Since the minimum-path dimension does not reflect the degree of overall vascularization but rather the scale-invariant tortuosity of single vascular paths, the constant minimum-path dimension seems to imply that the determinant of the elevated minimum-path dimension (e.g., substrate heterogeneity — see Chapter 6) remained largely unchanged throughout the measurement period.

As this thesis was nearing completion, a regressing tumor model (Shionogi mammary carcinoma in SCID mice) was being developed in our lab. Preliminary results of fractal dimensions during tumor regression ($n = 2$) are described in Appendix C.

4.3 Verification of Fractal Range

As detailed in section 3.4 the fractal dimension is measured by fitting a straight line to a logarithmic plot of a measure of mass² as a function of ruler size ($\ln r$). However, in nature there is only a limited range over which this linear relation holds. Figure 4-4a shows a typical logarithmic plot of measurement results obtained by the box-counting algorithm. Two gross observations can be made:

- For large r we see that $N(r)$ is constant, due to the finite size of the image.
- For small r we see that the slope $\frac{dN(r)}{dr}$ is no longer constant and gradually decreases. This is due to finite vessel-to-vessel distances (the average distance between capillaries is rarely below $50 \mu\text{m}$).

²This can be a direct measure of mass as in the sandbox method ($\ln M_r$), or an indirect measure as in the box-counting method ($\ln N_{box}$).

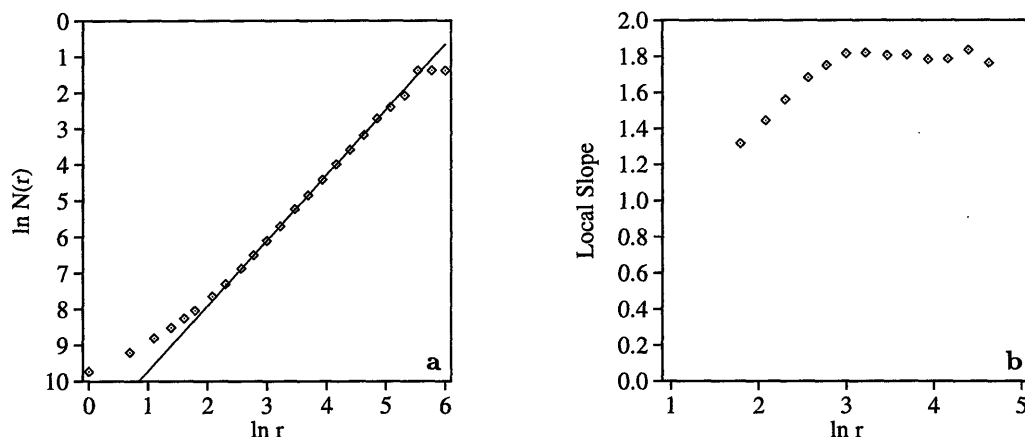


Figure 4-4: The plots used for determination of fractal dimension and range. (a) Logarithmic plot of number of occupied boxes ($\ln N(r)$) as a function of box-size ($\ln r$) and its linear fit; (b) Plot of the local slope as a function of box-size ($\ln r$). The local slope was calculated for each series of five consecutive points. These plots were derived from analysis of the SCC7 vascular network shown in Figure 3-3. The slope of the linear fit yields a box-counting dimension of $d_{box} = 1.81 \pm 0.01$.

These observations underscore the importance of verifying the fractal range (i.e., the linear range of the logarithmic plot).

The fractal range can be verified by plotting the local slope of the plot against the ruler size ($\ln r$), as shown in Figure 4-4b. The local slope can be calculated by fitting two or more consecutive points to a straight line. In Figure 4-4b five consecutive points were used to calculate the local slope. The flat part of the plot delineates the fractal range. Furthermore, this plot is a useful tool for uncovering slow crossover phenomena³.

In the vascular networks observed, fractal ranges were invariably limited by capillary-to-capillary distances, giving a lower cutoff of approximately $50 \mu\text{m}$. For normal capillary networks the theoretical upper cutoff would be the macroscopic length scale of the tissue, since capillary networks must be space-filling. In practice, this upper cutoff is determined by the image size.

For normal arteriovenous networks, one would expect a crossover from DLA-like scaling to compact scaling, because maximal artery-vein distances are determined by the distance that blood can travel through the capillary network before it is depleted of oxygen. This distance is on the order of several millimeters in skeletal muscle [105, 123], similar to the size of the whole image. Hence, no crossover was observed in the arteriovenous data.

For tumor networks, there is no good intuition for the upper bound of the fractal range. The measurements show that tumors are fractal below approximately $900 \mu\text{m}$, yet no crossover phenomena was observed for tumors, because above $900 \mu\text{m}$ the finite image size introduces non-negligible

³For example, if the plot would never flatten, but would slowly slope upwards toward a value of 2.0, we could say that there is crossover to a compact structure. However, such crossover behavior was not observed.

artifacts into the results.

4.4 Statistical Significance of Results

The separation of vascular networks into three classes of scale invariant behavior is clearly evident in Figure 4-1. Nevertheless, this separation should be formalized using appropriate unpaired statistical comparison tests. Two unpaired comparison tests were used for significance testing: the unpaired t-test and the Mann-Whitney U-test (described in section 3.5).

4.4.1 Between and Within-Class Separation

The data from Figure 4-1 were divided into five pairs of groups. The first three pairs were used to measure between-class separation and consisted of all possible pairings of the groups:

- Arteriovenous networks — normal subcutaneous and bone-induced networks in nude mice ($n = 22$).
- Tumor networks — tumor networks in nude and C3H mice ($n = 21$).
- Capillary networks — normal capillary networks in nude mice ($n = 12$).

The last two pairs were used to measure within-class separation within the arteriovenous network class and within the tumor network class:

- Bone-induced arteriovenous networks in nude mice ($n = 10$) vs. subcutaneous arteriovenous networks in nude mice ($n = 12$).
- LS174T tumor networks in nude mice ($n = 12$) vs. various tumor networks in C3H mice ($n = 9$).

All tests were performed for three different fractal dimensions: box-counting dimension, sandbox dimension, and minimum-path dimension. The results are summarized in Table 4.2.

Between-Class Separation

The p -values in Table 4.2 show that both the box-counting dimension and the sandbox dimension clearly separate the three classes of two-dimensional vascular networks observed: normal arteriovenous networks, normal capillary networks, and tumor networks. The minimum-path dimension is useful in distinguishing tumor networks from normal networks. Normal arteriovenous and capillary networks, however, have statistically similar minimum-path dimensions.

Table 4.2: Vascular Network Class Separation Based on Fractal Measurements

Network Classes	Box-Counting		Sandbox		Minimum-Path	
	M-W	t-test	M-W	t-test	M-W	t-test
Tumor vs. Capillary	$p < 0.0001$	$p < 0.0001$	$p < 0.0001$	$p < 0.0001$	$p < 0.0001$	$p < 0.0001$
Tumor vs. A-V	$p < 0.0001$	$p < 0.0001$	$p < 0.0001$	$p < 0.0001$	$p < 0.0001$	$p < 0.0001$
A-V vs. Capillary	$p < 0.0001$	$p < 0.0001$	$p < 0.0001$	$p < 0.0001$	$p = 0.8854$	$p = 0.9681$
Bone A-V vs. S.C. A-V	$p = 0.0240$	$p = 0.0006$	$p = 0.0479$	$p = 0.0788$	$p = 0.6444$	$p = 0.7128$
Tumor (nude) vs. Tumor (C3H)	$p = 0.8312$	$p = 0.6966$	$p = 0.1356$	$p = 0.2372$	$p = 0.1769$	$p = 0.1443$

Within-Class Separation

The p -values in Table 4.2 show that the box-counting dimensions of bone-induced and subcutaneous arteriovenous networks are not statistically similar, and that their sandbox dimensions are marginally similar. The mean differences of 0.05 for d_{box} and 0.03 for d_{sand} , are most likely due to the difficulty of keeping all arteries and veins on the curved bone surface in focus (see subsection 4.1.1). The minimum-path dimensions of these two types of arteriovenous networks are statistically similar.

Fractal dimensions for tumor networks in nude mice (LS174T tumors) and tumor networks in C3H mice (MCAIV, SCC7 and Sa1 tumors) are statistically similar. This observation suggests that the fractal dimensions for two-dimensional tumor networks are relatively independent of host and tumor type.

4.4.2 Effect of Imaging Method

A separate series of measurements was performed in normal arteriovenous networks in SCID mice. The imaged networks were divided into two groups. The first group ($n = 12$) was imaged using transmitted light microscopy, and the second group ($n = 11$) was imaged using fluorescence microscopy (see section 3.2). The fractal dimensions of the two groups were compared statistically. The comparison results appear in Table 4.3. These results show that there are no significant differences in fractal dimensions due to the use of transmitted light or fluorescence microscopy⁴.

⁴It should be noted that measurements of vessel diameter are known to be sensitive to imaging method [81]. These differences are presumably due to the plasmatic zone between erythrocytes and the vessel wall, and hence should have no effect on fractal dimension measurements.

Table 4.3: Effect of Imaging Method on Fractal Dimension

Imaging Methods	Box-Counting		Sandbox		Minimum-Path	
	M-W	t-test	M-W	t-test	M-W	t-test
Trans. Light vs. Fluorescence	$p = 0.9999$	$p = 0.8546$	$p = 0.2423$	$p = 0.4690$	$p = 0.1962$	$p = 0.1028$

4.5 Discussion

The separation of vascular networks into three classes based on fractal measurements has important implications, because these classes correspond to different statistical growth processes (see section 2.3).

4.5.1 Normal Vascular Networks

The measurements in normal arteriovenous networks are in concert with the fractal dimensions of two-dimensional diffusion-limited aggregates ($d_f = 1.71$ and $d_{min} = 1.0$) [91, 131]. These results agree with previously published fractal measurements of retinal arterial and venous networks⁵ [28, 72, 82], the retinal vasculature being a routinely observed naturally occurring two-dimensional network.

On the face of it, these results seem consistent with the accepted view of the angiogenic process, where growth factors initially diffuse from low-nutrient or hypoxic regions and induce growth. Under such circumstances, the diffusion-limited behavior of the arteriovenous network is quite understandable. This explanation, however, is fatally flawed because angiogenesis does not seem to occur on the artery-vein level. Rather, vascular growth occurs at the capillary or post-capillary level [20, 33, 88].

This vascular growth (on the capillary and post-capillary level) does not, however, form diffusion-limited structures. Neovascularization studies [2, 20, 88] have shown that newly formed capillaries grow in a compact mesh and not in a tree-like structure, contrary to the expected structure in diffusion-limited growth. Our measurements corroborated these observations by showing that the normal subcutaneous striated muscle capillary bed is also a compact structure. These observations

⁵There is one account [23] which claims that retinal vessels display percolation-like scaling. That account, however, was not peer-reviewed and used only the correlation method for measuring fractal dimension. Another account [72] claimed that at high resolution (small r) there is a crossover to another fractal domain with $d_f \approx 1.2$. This is most likely due to a misinterpretation of the logarithmic plot (such as the one in Figure 4-4a). This misinterpretation can be avoided by examining the local slope, as shown in Figure 4-4b. The authors of that particular study did not take this extra precaution.

In a paper on the modeling of arterial networks as minimum energy dissipation vascular systems [128], it was claimed that arterial networks are space-filling, and that fractal dimensions of $d_f < 2$ are a crossover effect. This claim was based on the assumption that distances between the ends of adjacent terminal arterioles are equal for all terminal arterioles in a network. Experimental evidence indicates that this assumption is clearly wrong [105]. The distance between the ends of adjacent terminal arterioles is bounded from above by the distances which erythrocytes can travel before their oxygen is depleted in the capillary network (typically several millimeters), and from below by the capillary spacing (typically $50 \mu\text{m}$). My measurements were all carried in the range bounded by those values. Clearly, on the whole-organ scale the arteriovenous network can be viewed as space-filling.

are also supported by many published images of normal capillary beds including lung capillary bed [83], colon capillary bed [124], ocular capillary beds [37, 70, 112], cardiac and skeletal muscle capillary beds [107], and the chorioallantoic capillary bed [16].

Clearly, we need to explain what causes the capillary networks to attain a compact structure. How can we settle this apparent contradiction between the commonly accepted hypothesis that growth factor diffusion initiates the angiogenic process and the observation that newly growing capillaries form a compact structure? This issue will be dealt with in Chapter 5.

4.5.2 Tumor Vascular Networks

The fractal measurements in tumor vasculature show that the tumor vessels do not form a compact structure, but are consistent with measurements for the critical percolation cluster ($d_f = 1.896$ and $d_{min} = 1.13$) [50, 127]. This observation represents the first evidence for a biological growth process whose key determinants are local properties. Furthermore, measurements of fractal dimension over time indicate that the percolation-like nature of tumor vascular networks is not a transient phenomenon. Tumor vascular networks, like percolation clusters, are characterized by loops and avascular areas of many different length scales (see Figures 3-2, 3-3, 4-2c, and References [1, 68, 76]). Percolation being a local growth process [131] suggests that there exists some local substrate property which determines tumor capillary growth. Three biological observations suggest that this local property can be hypothesized to be matrix inhomogeneity. First, tumor tissue does not possess the regular periodic geometry formed by cells in normal tissue, and has different phenotypic subpopulations. Second, extracellular matrix (ECM) is a larger and more heterogeneous component of tumor tissue compared to normal tissue [49, 59, 99, 129]. Third, “blood channels”, blood pathways through tissue not lined by endothelium, have been observed in tumors [60]. Such channels can be viewed as evidence of percolation phenomena through the ECM. This hypothesis and its compatibility with the normal vascular growth model will be explored in Chapter 6.

Chapter 5

Modeling Normal Capillary Network Growth

In subsection 4.5.1 I detailed the fundamental problem in modeling normal capillary network growth. The problem lies in the apparent contradiction between the commonly accepted hypothesis that growth factor diffusion initiates the angiogenic process and the observation that the newly growing capillaries form a compact structure. While diffusion is inevitably a component in the process of vascular growth (see Figure 2-1), a compact structure is no longer diffusion-limited because the diffusion field is “masked”, so the growth becomes insensitive to variations in the diffusion gradient.

We therefore need a new mechanism that causes growth factor concentration to increase throughout the growth perimeter, thus “masking” the diffusion field and promoting uniform growth. Conceptually, the source of growth factors near the growth perimeter could either be the hypoxic tissue [93, 121] or the growing structure itself. If the source is solely the hypoxic tissue, high growth factor concentrations near the growth perimeter could be achieved if the rate of growth factor reception or removal at the growth perimeter is slow compared to the diffusion rate. In biological terms, this can be achieved by the existence of low-affinity receptors, for example. In physical terms, it is tantamount to a *low interaction probability* between growth factors and the growing structure. If, however, the main source of growth factors near the growth perimeter is the growing structure itself, then at each growth site we have a *local amplification* of growth factor which then propagates to neighboring sites. In biological terms, local amplification of growth factor levels can be achieved by autocrine or paracrine release of growth factors [34, 35], or by the release of growth factors sequestered in the endothelial basement membrane [21, 35]. In physical terms, it is tantamount to a process where a growth event is accompanied by a uniform increase of growth probability in sites neighboring the growth site.

The above hypotheses for capillary network formation were compared using a growth model.

5.1 Basic Growth Model

The basic growth model incorporated diffusion of growth factor and vascular growth in response to growth factor reception, in the presence of either a low interaction probability (i.e., the “low affinity hypothesis”) or local amplification (i.e., the “autocrine hypothesis”). The growth model was implemented according to the following rules:

- Growth begins at a single central seed.
- Growth factor “particles” diffuse from points removed at least some minimum distance from the structure.
- When a “particle” hits the growing structure it is taken up with a preset probability p_i .
- All uptaken particles are recorded as “hits” within a fixed time period.
- At the end of the period growth occurs at all hit sites.
- If there is local amplification, F additional particles are released at each growth site. F is the “local amplification factor”.
- There is a fixed growth factor production rate per unit area of “hypoxic” tissue.
- The model is implemented on a 128×128 square lattice with periodic boundary conditions, unless otherwise noted.

The source code for the model, including the parameters used in all later enhancements of the model, is listed in section A.6.

5.2 Local Amplification vs. Low Interaction Probability

The model presented in section 5.1 was used to examine whether the local amplification mechanism or the low interaction probability mechanism could account for the compact structure of normal capillary networks. The results are shown in Figure 5-1. One can observe that for $p_i = 1$ and no local amplification the classic diffusion-limited structure is obtained. As p_i is decreased the structure becomes more compact and regular. When local amplification is activated, a compact structure is obtained for $F > 1$. We can therefore conclude that either of these mechanisms, if strong enough, can lead to the formation of a compact capillary network.

We can assess which of the two mechanisms is a more likely determinant of the compact structure by examining two parameters as a function of fractal dimension, as seen in Figure 5-2 (the closer the fractal dimension is to 2.0, the closer the model network is to being compact).

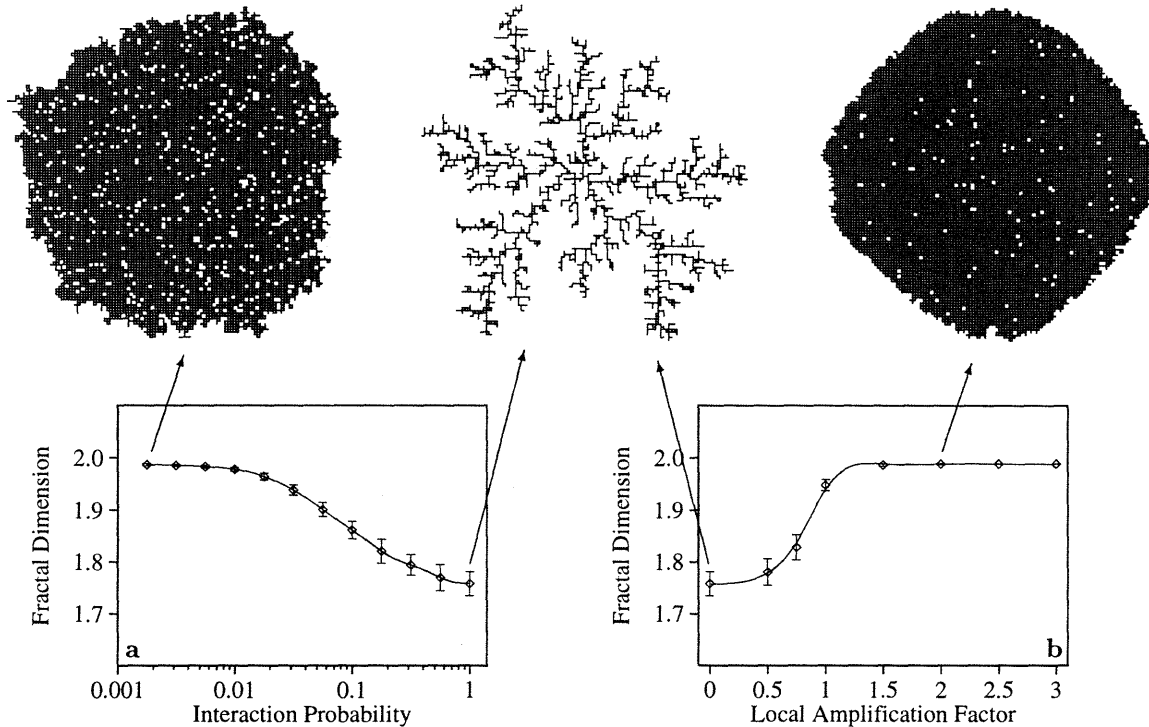


Figure 5-1: Effects of (a) low interaction probability and (b) local amplification on fractal dimension.

The first parameter, the growth time per unit mass, is obtained by dividing the total growth time (in arbitrary model time units) by the number of occupied lattice sites in the final structure. It is motivated by the reasoning that there is an advantage in growing blood vessels relatively fast towards the hypoxic region.

The second parameter, the growth efficiency, is motivated by the reasoning that in order for growth to be efficient, the hypoxic tissue should produce as little growth factor as possible to induce the formation of new capillaries. The growth efficiency is obtained by dividing the total number of growth factor particles originating beyond the network by the number of occupied lattice sites in the final structure.

Although at first thought the two parameters may seem to work in opposite directions, they do not. Figure 5-2a shows that when the interaction probability is lowered, growth time per unit mass does not change significantly; but when local amplification is incorporated, the growth time per unit mass for a compact structure decreases by an order of magnitude. Figure 5-2b shows that with local amplification, compact growth efficiency increases by more than an order of magnitude, compared to no significant change in growth efficiency when low interaction probability is incorporated.

Another approach to comparing the two mechanisms is to measure the percentage of unoccupied lattice sites within the structure perimeter. This value is an indicator of the number of poorly vascularized areas which a given mechanism would create. For compact structures with similar

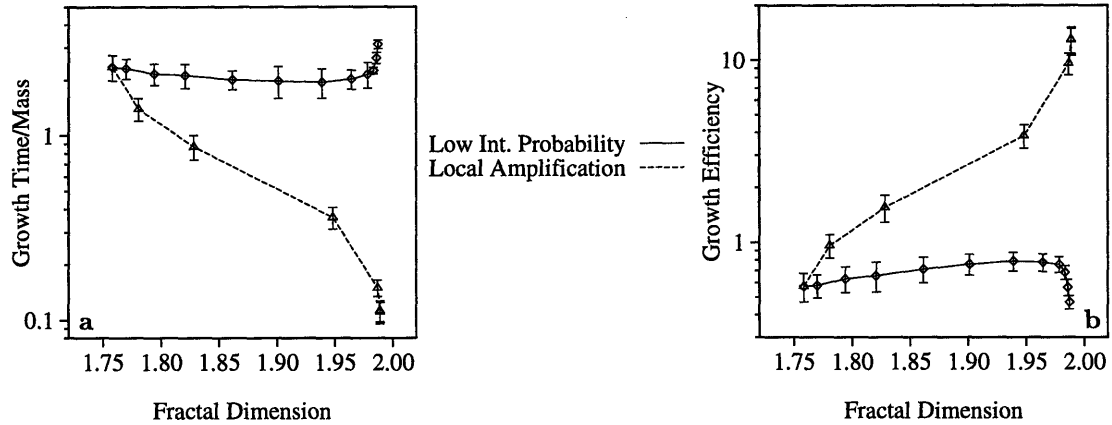


Figure 5-2: Comparison of the local amplification and the low interaction probability mechanisms: (a) growth time per unit mass and (b) growth efficiency. Clearly, growth with the local amplification mechanism is both faster and more efficient as the fractal dimension nears 2.0.

fractal dimensions ($d_f \approx 1.99$), the percentage of lattice sites left unoccupied with the low interaction probability is approximately 5%, and with the local amplification mechanism less than 1%.

In view of these results, it seems reasonable to suggest that local amplification, corresponding to the biological autocrine mechanisms of growth factor release, is the key determinant of the observed compact shape of normal capillary networks.

This suggestion is corroborated by several pieces of experimental evidence. A recent study of rabbit corneal endothelial cells [69], provided evidence showing the existence of an autocrine growth mechanism utilizing PDGF. A previous study showed that capillary endothelial cells express bFGF, and raised the possibility that the formation of new capillaries is induced by the endothelial cells themselves [113]. Furthermore, a study of low-affinity bFGF binding sites in a variety of cells ranging from baby hamster kidney cells to bovine capillary endothelial cells [96], showed that these binding sites are most likely cell-associated heparin-like molecules and that only high-affinity binding sites stimulated plasminogen activator production by bovine capillary endothelial cells, thus suggesting that only the high-affinity binding sites are receptors mediating growth stimulus.

In an attempt to corroborate experimentally the existence of an autocrine mechanism for endothelial cell growth, we performed a series of in vitro experiments. In these experiments bFGF was administered to endothelial cells in a culture dish either in a single dose, which created a uniform concentration in the dish, or by controlled release, which presumably created a gradient in the dish. If an autocrine mechanism was at work, one would expect the growth patterns in both cases to look similar and have little directional dependence. Indeed, this was the outcome (see Appendix D for details). Recently, however, a much more elegant in vitro experiment was published [48], which showed the existence of an autocrine mechanism for angiogenesis. In that experiment, mouse aortic endothelial cells were stably transfected with a retroviral expression vector harboring a human

bFGF cDNA. The transfected cells showed marked sprouting activity in vitro, forming networks of cord-like structures. Remarkably, this activity was suppressed by administration of anti-bFGF antibodies, thus revealing the autocrine nature of the angiogenic process [48].

5.3 Model Units and Reality

The model proposed in section 5.1 seems to do a good job in explaining the observed shape of capillary networks. However, it still remains to be proven that model parameters and results are consistent with physiological behavior when translated into “real-life” units. The following calculations are presented for this purpose.

The lattice constant a of the model lattice, representing the minimal vessel-to-vessel distance, can be reasonably assumed to be in the lower range of naturally observed capillary-to-capillary distances [123]:

$$a \approx 50 \mu\text{m} \quad (5.1)$$

The diffusion constant in tissue of a growth factor such as VEGF (molecular weight ≈ 45000) can be approximated as [12]:

$$D \approx 5 \cdot 10^{-7} \text{ cm}^2/\text{sec} \quad (5.2)$$

If the length unit is taken to be the lattice constant a , then D becomes:

$$D \approx 2 \cdot 10^{-2} a^2/\text{sec} \quad (5.3)$$

Therefore, the time it takes a particle to “explore” a unit lattice cell of area a^2 is on the order of:

$$\sqrt{\frac{a^2}{D}} \approx 50 \text{ secs} \quad (5.4)$$

In the model, 1 unit of model-time (umt) equals the time it takes to advance a particle one lattice constant a . In real units, this would therefore be on the same order as the time in Equation 5.4. Hence:

$$1 \text{ umt} \approx 50 \text{ secs} \quad (5.5)$$

The model lattice is approximately 100×100 units, or in real lengths (Equation 5.1): $5 \times 5 \text{ mm}^2$. The time t_0 it takes to grow a vascular network of such dimensions can be reasonably estimated as [77, 78, 119, 134]:

$$t_0 \approx 10^6 \text{ secs} \quad (5.6)$$

which is equivalent to 11.5 days. In a compact structure (as capillary networks are), virtually every

site is occupied. Therefore, the growth time per unit mass (or area), in real time, would be:

$$g_{real} \approx \frac{t_0}{100 \times 100} = 10 \text{ secs}/a^2 \quad (5.7)$$

In Figure 5-2a we saw that the model yielded a value of:

$$g_{model} \approx 0.1 \text{ umt}/a^2 \quad (5.8)$$

Are these two values comparable? Indeed they are. In Equation 5.5 we defined 1 umt as approximately 50 secs. Therefore:

$$g_{model} \approx 5 \text{ secs}/a^2 \quad (5.9)$$

which is of the same magnitude as g_{real} (Equation 5.7). Keeping in mind the approximations made in the process, it is notable that the two values for g are so close.

In summary, we see that the model and its parameter estimates produce results which are in concordance with physiological values. This concord lends further credence to conclusions drawn from the model.

5.4 Model Evaluation

The model offered in this chapter rests on two pillars. First, it attempts to reproduce the observed scale-invariant properties of capillary networks. Second, it is based on accepted physiological phenomena, such as growth factor diffusion and autocrine growth factor release mechanisms. Most previously reported models have failed to incorporate either one or both of these elements [9].

Virtually all previously proposed models have ignored the apparent paradox between the compact nature of the capillary network and the supposedly key role of growth factor diffusion in angiogenesis [9]. Some models [47, 71] have gone as far as assuming that capillaries grow in a tree-like branching network, an assumption that is clearly contradicted by most experimental evidence. Arterial and venous networks indeed display a morphology reminiscent of diffusion-limited processes, but these networks form by the remodeling of existing vessels and not by formation of new ones (see Chapter 7).

The model presented in this chapter does not assume a specific mechanism of capillary tube formation. Some models have been based on a particular mechanism, such as sprouting [8], although there is another mechanism — intussusception — which may be involved in capillary tube formation [15, 103]. The model proposed here is equally valid when either sprouting or intussusception is assumed as the mechanism of capillary tube formation.

This model is also unique in offering a clear distinction between normal and tumor capillary

network formation (see Chapter 6). Other models tended to blur this distinction [8]. This was due to the fact that until the present study, the unique scale-invariant properties of tumor networks were not known, and there seemed to be no need for different growth models for normal and tumor capillary networks. This model allows, for the first time, to differentiate the key determinants of normal and tumor capillary network formation.

Clearly, this model provides information about only a small subset of the properties of newly forming capillary networks. Other models, based on ad-hoc growth rules, have tried to reproduce other properties such as branching angle distribution [66]. Since this model is founded on basic physiologic phenomena and does not delve into the minutiae of the physiologic mechanisms involved, it is limited in the scope of the properties it can predict or reproduce without resorting to ad-hoc assumptions or rules. However, the model fully meets the goals of this research to uncover the key determinants of vascular network formation. The analysis in the preceding sections has shown that when growth factor diffusion is combined with an autocrine mechanism of growth factor release by endothelial cells, a compact capillary network is obtained. Furthermore, the analysis has shown that an autocrine mechanism is a relatively efficient and fast mechanism for capillary growth, and that the model's growth rates are in order-of-magnitude agreement with "real-life" growth rates.

Chapter 6

Modeling Tumor Network Growth

In subsection 4.5.2 we saw that the measured fractal dimensions of tumor vascular networks are consistent with the fractal dimensions of the critical percolation cluster. Percolation being a local growth process [131], suggested that there exists some local substrate property which determines tumor capillary growth. Biological observations suggest that this local property can be hypothesized to be extracellular matrix inhomogeneity (see subsection 4.5.2). In order to examine this hypothesis, the previous growth model (see section 5.1) was modified so that a randomly selected subset of all lattice sites became inaccessible to growth.

6.1 Growth Model Modification

In the modified version of the growth model, each lattice site is assigned a random number R in the range $[0,1]$. Growth occurs at all particle reception sites where $R < T$. T is a preset number in the range $[0,1]$ and represents the fraction of lattice sites which are accessible to growth (T is also called the “accessibility”, and reported as a percent). If no site with $R < T$ is available for growth in a given cycle, growth occurs at the site with the lowest R ($R > T$). The local amplification mechanism is taken into account as described in section 5.1.

6.2 Model Results

The model results are shown in Figure 6-1. Two important points are evident in these results.

First, we see that as the threshold T drops and more sites become inaccessible to growth, the transition zone between the compact phase and diffusion-limited phase becomes larger and more blurred. Furthermore, an increasing local amplification factor (F) is required to achieve a given fractal dimension as T decreases. Theoretically, below the site-percolation threshold for a square lattice ($T < 0.6$), a compact structure cannot be achieved even as $F \rightarrow \infty$. In reality, F is finite and

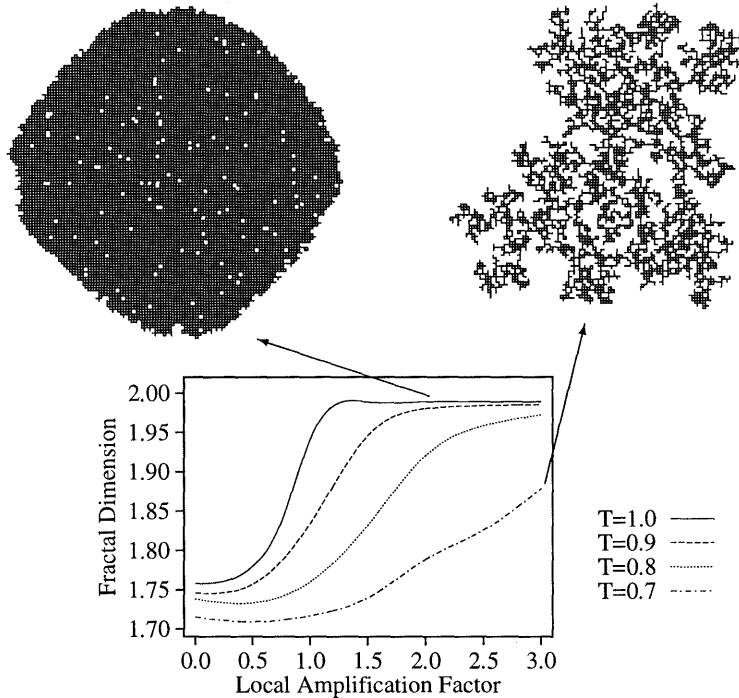


Figure 6-1: Effect of substrate inhomogeneity on fractal dimension. The different curves represent different degrees of inhomogeneity as represented by the accessibility parameter T . The lines represent cubic splines with a smoothing parameter $s_p = 0.9995$ (see section 3.7). Error bars were omitted for clarity. Note that the line with $T=1$ is the same line as in Figure 5-1b.

not every lattice site is necessarily explored at each growth cycle so that for $F = 3$, for example, $T \leq 0.7$ is sufficient to ensure a percolation-cluster type of vasculature.

Second, we see that without local amplification, the structure remains diffusion limited with $d_f \approx 1.7$, relatively insensitive to variations in the accessibility T . This observation further emphasizes the possible importance of the local amplification (i.e., autocrine) mechanisms in normal and tumor vascular network formation. Figure 6-1 demonstrates that in the presence of local amplification ($F = 3.0$) and 30% inaccessibility, a non-compact structure reminiscent of tumor vasculature was obtained.

6.3 Correlation with Biological Observations

The model results are quite striking in showing that the modification of a single parameter in the normal growth model leads to the formation of pathological-looking networks, similar in appearance and fractal characteristics to tumor vascular networks. In subsection 4.5.2 the hypothesis was advanced that this parameter (substrate inhomogeneity) is associated with matrix properties in tumors. The question now arises whether there exists any experimental evidence which demonstrates that changes in the extracellular matrix (ECM) can indeed modify angiogenesis. The answer is

positive.

It is well-known that when endothelial cells are cultured in a collagen gel they reorganize into a network of capillary-like tubes [94]. Recent in vitro studies of endothelium–ECM interactions have shown that ECM molecules have the ability to induce endothelial cell differentiation and growth by chemical and mechanical means [22, 58]. Chemically, the binding of transmembrane integrin receptors induces these effects. Mechanically, the effects are mediated by the resistance to cell-generated loads applied to the integrin receptors. One such study showed that as fibronectin concentrations in culture are increased, endothelial cell proliferation rate increases too [57] (fibronectin is a constituent of the ECM). Another study demonstrated that in vitro capillary tube formation can be modified by the application of anti-integrin antibodies [39].

Recent in vivo studies on the control of angiogenesis by the extracellular matrix also support the model. In one study [135] the local composition of the ECM was manipulated by varying the GM3:GD3 ganglioside ratio in the rabbit cornea. The study showed that these variations could either stimulate or repress angiogenesis. Another study [13] showed that by administering an antagonist to integrin $\alpha_v\beta_3$, the most promiscuous of the integrin family, ECM interaction with endothelial cells was inhibited and angiogenesis repressed.

6.4 Conclusions

The main conclusion from the model is that substrate inhomogeneity may be a key determinant of tumor vascular network formation. The studies cited in section 6.3 show this conclusion to be consistent with known properties of the ECM. This conclusion implies that in order to modify tumor vasculature significantly, the underlying substrate properties must also be modified. However, modification of the ECM may have two effects with uncertain therapeutic implications. On the one hand, if ECM inhomogeneity is reduced, vascular network formation will be more uniform, and the extent of the avascular areas will diminish. This may improve nutrient supply to tumor cells, but it will also assure a more homogeneous delivery of therapeutic agents. On the other hand, if ECM inhomogeneity is increased, the extent of the avascular areas will be greater, more tumor cells will be deprived of nutrients, but the delivery of therapeutic agents to tumor cells may be hampered. These contradictory effects may be part of the reason why tumors display an enormous variability in their responses to therapeutic interventions.

While it is uncertain whether this model’s conclusions can be extended to other forms of pathological angiogenesis, it should be noted that some of the architectural features of tumor vasculature (e.g., increased avascular areas) are also present in other states of abnormal neovascularization such as diabetic retinopathy [3].

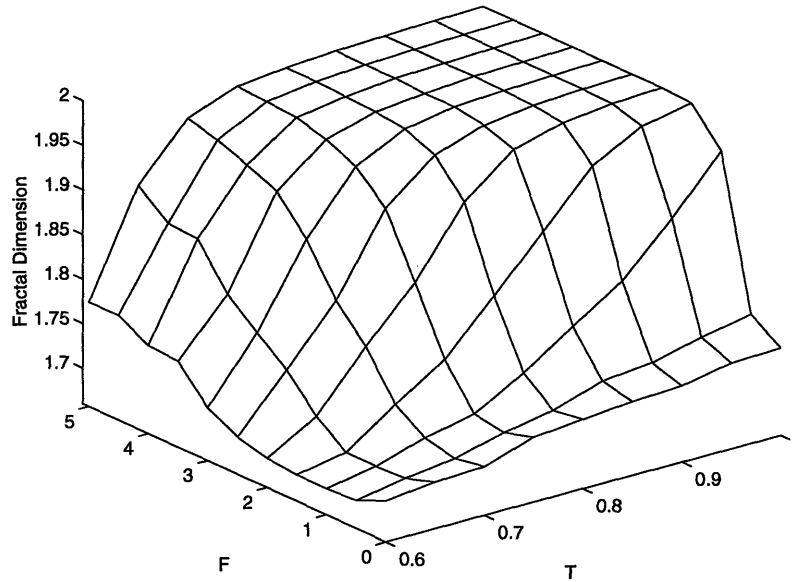


Figure 6-2: Fractal dimension as a function of model parameters. The horizontal axis represents the level of substrate inhomogeneity as expressed by the substrate threshold parameter T . The vertical axis represents the local amplification factor F .

6.5 Evaluation and Comparison with “Classic” Percolation

The growth model described in this chapter differs from “classic” percolation growth models such as spreading percolation and invasion percolation [131] in several important aspects. In traditional percolation models every perimeter site is a potential candidate for growth. In the model described in this chapter, some perimeter sites may be excluded from consideration in a particular growth cycle because they did not receive any growth factor “particles”. This means that the threshold parameter T in this model is not equivalent to the threshold probability p in percolation [127]. An effective threshold probability p can be associated with this model, and it is generally less than T , unless we can assure that every perimeter site is explored (i.e., when the local amplification factor F is high, since $\lim_{F \rightarrow \infty} T = p$).

The interplay of the local amplification factor F and the substrate inhomogeneity T provides a large domain in which percolation-like scaling can be observed. Figure 6-2 shows a surface plot of fractal dimension as a function of substrate inhomogeneity (T) and local amplification (F). Two trends are evident in this plot. First, the fractal dimension increases as inhomogeneity decreases (i.e., as $T \rightarrow 1.0$). This trend is expected from well-known percolation properties [127]. Second, the fractal dimension increases as the local amplification factor F increases. This trend can be understood by noting that an increase in F is tantamount to an increase in the effective threshold probability p .

By calculating the contour lines which correspond to the domains of scale invariance described in

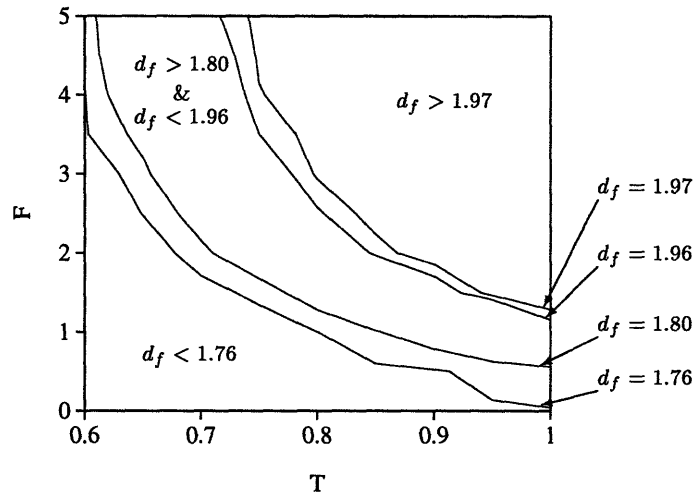


Figure 6-3: Fractal domains as a function of model parameters. The horizontal axis represents the level of substrate inhomogeneity as expressed by the threshold parameter T . The vertical axis represents the local amplification factor F . The contour lines separate this two-dimensional space into three morphological domains: compact ($d_f > 1.97$), tumor-percolation ($1.80 < d_f < 1.96$) and tree-like ($d_f < 1.76$). The contour line values were chosen at two standard deviations from the experimentally observed values (see Chapter 4).

Chapter 4, one can see how this model helps explain the large variations observed in tumor networks. Figure 6-3 shows contour lines drawn at two standard deviations from the observed fractal dimensions in normal capillary, normal arteriovenous, and tumor networks (see Chapter 4). These contour lines divide the T - F space into three domains with thin transition zones between them. Figure 6-3 illustrates that a normal capillary network (i.e., compact) morphology can be achieved even when the substrate is not perfectly homogeneous, provided the local amplification mechanism is strong enough to push p well above the percolation threshold. Furthermore, it illustrates that within the tumor network morphology domain small variations in local amplification or substrate inhomogeneity can lead to relatively large variations in fractal dimensions. This observation provides a possible explanation as to the reason why the standard deviation of fractal dimension measurements in tumor networks is 4 times that of normal capillary networks (see Chapter 4).

The variability in tumor network characteristics can be further explored by plotting the minimum-path dimension as a function of substrate inhomogeneity (T) and local amplification (F), as shown in Figure 6-4. Two trends are evident in this plot. First, the minimum-path dimension decreases as inhomogeneity decreases (i.e., as $T \rightarrow 1.0$). Second, the minimum-path dimension decreases as the local amplification factor F increases. These trends can be understood by noting that either an increase in F or an increase in T makes more sites effectively available for growth, thus reducing the average length of a path between any two points. Figure 6-5 shows a contour line corresponding to

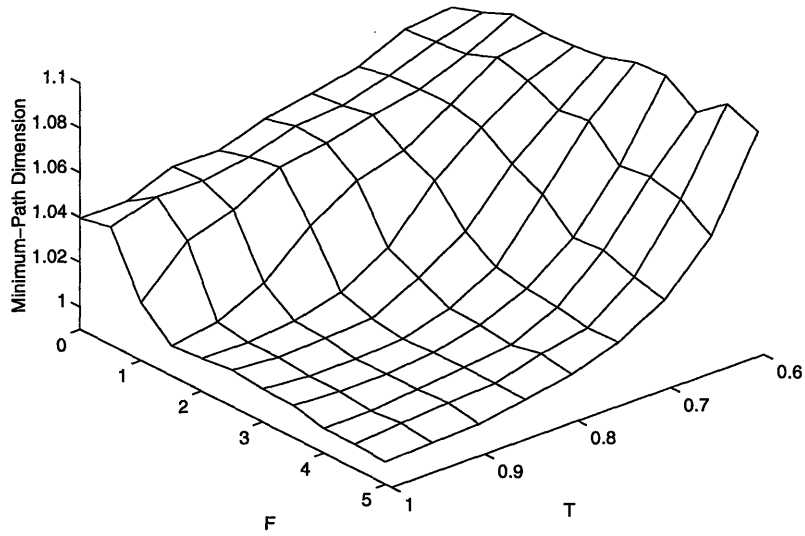


Figure 6-4: Minimum-path dimension as a function of model parameters. The horizontal axis represents the level of substrate inhomogeneity as expressed by the threshold parameter T . The vertical axis represents the local amplification factor F . Note that the T and F axes are reversed in comparison with Figure 6-2.

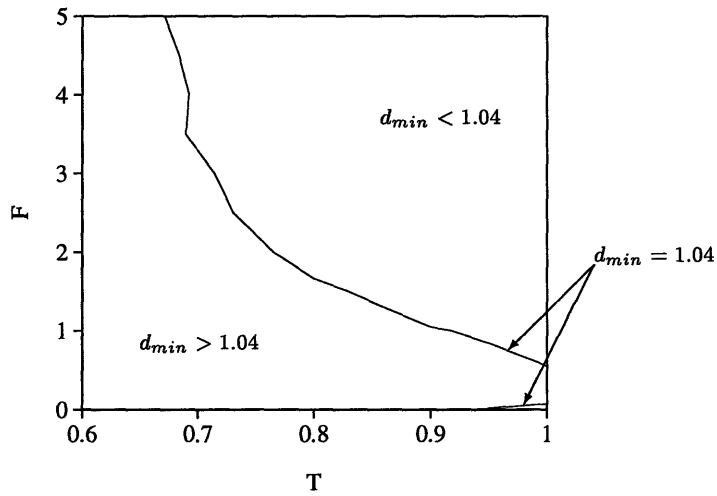


Figure 6-5: Minimum-path domains as a function of model parameters. The horizontal axis represents the level of substrate inhomogeneity as expressed by the threshold parameter T . The vertical axis represents the local amplification factor F . The contour lines separate this two-dimensional space into two morphological domains: straight ($d_{min} < 1.04$) and tortuous ($d_{min} > 1.04$). The contour line value was chosen at two standard deviations from the experimentally observed value for normal networks (see subsection 4.1.2).

$d_{min} = 1.04$, a value which is two standard deviations above the observed d_{min} of normal capillary networks. This contour line separates the T - F space into two morphological domains — a “straight” vessel domain and a “tortuous” vessel domain. Furthermore, this contour line splits the tumor network domain in Figure 6-3 into two nearly equal parts. By doing so it provides an explanation to the observation that the minimum-path dimension variance in tumors is 4 times that of normal networks (see Chapter 4). Figure 6-5 also points out that a large part of the domain with $d_f < 1.76$ in Figure 6-3 does not correspond to “classic” DLA structures. While a tree-like morphology is often observed in this domain, the structures tend to be much more tortuous than DLA clusters. The significance of this domain for the formation of capillary networks is rather limited, however, because tree-like capillary networks are very rare in nature [89].

It should be noted that the contours in Figures 6-3 and 6-5 are not exact, since the fractal dimensions of the model networks were calculated with a standard error of 2% (or less). Although the position of the contour lines may shift slightly, the qualitative results and conclusions are not affected.

Chapter 7

Modeling Arterial and Venous Network Growth

In subsection 4.1.1 we saw that the fractal dimensions of arteriovenous networks are consistent with the fractal dimensions of DLA clusters. As discussed in subsection 4.5.1, these results may seem consistent with the previously accepted view of the angiogenic process where growth factors initially diffuse from low-nutrient or hypoxic regions and induce growth. Under such circumstances, the diffusion-limited behavior of the arteriovenous network is quite understandable. This explanation, however, is flawed because angiogenesis does not seem to occur on the artery-vein level. Arteries and veins form by remodeling of existing capillaries.

However, if one thinks of the capillary mesh as a regular lattice (which it often appears to be — see, for example, Figure 2 in Reference [124]), one can view artery-vein formation as a remodeling process following Laplacian growth rules that occurs on a fully-occupied pre-existing capillary lattice. Indeed, experimental evidence has shown that arterialization occurs in the capillaries which are directly connected to the tips of the terminal arterioles [108] and not at random sites in the capillary mesh. If this is the case, one needs to explain what is the biological equivalent of the Laplacian field which governs the remodeling process. If one assumes, as the biological evidence suggests, that artery-vein formation is a slow process, which occurs after a capillary network has largely formed, then one cannot assume that arteries and veins respond to the same growth factors as do newly forming capillaries. There could be, however, certain growth factors which are potent mitogens for smooth muscle cells and not for endothelial cells. Therefore, one possibility for the Laplacian field is a diffusion field of such a growth factor, set up by the secretion of these growth factors in low-flow regions. DLA-based vascular growth models published to date [51, 71], have all implicitly assumed such a diffusion field.

There is also another possibility for the source of gradient-sensitive growth of arteries and veins. It

has been observed in many microvascular studies that the steepest pressure gradients in the vascular system occur in the terminal arterioles¹ [80, 136]. This observation may lead us to postulate that if the remodeling rate (length/time) is dependent on the pressure gradient in the vessel, we could have a situation analogous to the process of viscous fingering² [101]. Yet regardless of the biological source of the Laplacian field associated with the ramified structure of arteriovenous networks, a fundamental problem remains. When a compact capillary mesh remodels into a vascular tree, some vessels must be resorbed, since a vascular tree is different from a vascular mesh not only geometrically (e.g., vessel diameters) but also topologically (i.e., in its connectedness). All DLA-based growth models fail on this point because they ignore the issue of capillary resorption.

In this chapter I would like to present a possible mechanism for vessel resorption, based on acceptable biological assumptions. I do not intend to claim that this is the actual physiological mechanism, since there is no currently known way to validate such a claim. I simply intend to show that using a general assumption about the role of shear stress in vessel remodeling, it is possible to develop a novel (yet simple) model, under which a perturbation in shear stress can lead to divergent behavior of vessel diameter.

7.1 Role of Stress in Vessel Remodeling

The hypothesis that vessel growth and resorption may be linked to stress in the vessel has been advanced in the past, on the basis of three empirical observations [38]. First, transport through cell membranes depends on the strain in the membranes. Second, the behavior of actin and actin-myosin bridges is strain-dependent. Third, chemical reaction rates are dependent on pressure, stress and strain. In this context, Fung [38] postulated that there should be a homeostatic stress state, and that deviations from this state could lead to either growth or resorption (depending on direction and magnitude of stress change), subsequently returning the stress level to its homeostatic state. Recent molecular biologic studies [55, 98, 102, 122] lend further credence to the hypothesis that vessel growth may be stress dependent, by showing upregulation of growth factors, adhesion molecules, and other bioactive compounds in response to shear stress changes. There has also been one study showing that changes in circumferential wall stress could be responsible for arterial tree remodeling [109]. In the latter report, a model was proposed in which input pressure changes were shown to cause terminal arteriole formation or rarefaction by assuming a stress-dependent growth rule. In addition, a plethora of in vivo experimental evidence shows that hypertension can lead to vessel rarefaction [120].

¹Theoretically, it can be shown that in any vascular tree which obeys Murray's law [97], $Q \propto r^3$, the pressure gradient ∇P in a vessel is inversely proportional to the vessel radius r : $\nabla P \propto r^{-1}$.

²Viscous fingering occurs when a less viscous fluid is injected into a more viscous fluid under conditions in which the viscous forces alone determine the flow. Under such conditions a fingered interface emerges. It can be shown that the situation is analogous to Laplacian growth because the interface velocity is proportional to the interface pressure gradient ($\vec{v} \propto \nabla P$).

The existence of a constant homeostatic shear stress level in a vascular tree can also be derived [117] from Murray's law [97]. Murray's law states that if one minimizes the energy required to maintain flow in a given vessel segment, then the volumetric flow Q , obeys:

$$Q = kr^3 \quad (7.1)$$

where r is the vessel radius, and k is a constant depending on blood viscosity and endothelium metabolism. The average velocity in the vessel therefore obeys $\bar{v} \propto r$. If one assumes Poiseuille flow, then the velocity profile is given by:

$$v(x) = v_{max} \left[1 - \frac{(r-x)^2}{r^2} \right] \quad (7.2)$$

where x is the distance from the vessel wall. The shear stress at the wall ($x = 0$) is therefore:

$$\tau \propto \left. \frac{dv}{dx} \right|_{x=0} = \frac{2v_{max}}{r} \quad (7.3)$$

but since in Poiseuille flow $v_{max} = 2\bar{v}$, we see that the shear stress in all vessels obeying Murray's law is the same. Experimentally, many arterial systems obey Murray's law [118].

While the role of stress in vessel remodeling seems important, to date no model has been proposed for stress-based capillary network remodeling.

7.2 Shear-Stress Based Arterialization Model

Using the most general assumptions and trying to avoid ad-hoc growth rules, an arterialization model for a capillary lattice will now be advanced. In general, the model operates on a graph whose connectivity matrix is known. All capillary segments connecting adjacent nodes (i.e., lattice sites) are assumed to be of equal length L . Initially, all segments are also of equal diameter d . The conductance C_{ij} of a capillary segment between nodes i and j , assuming Poiseuille flow [80] and fixed viscosity (η) is:

$$C_{ij} = \frac{\pi d_{ij}^4}{128\eta L} \quad (7.4)$$

Designating P_i as the pressure at node i , the flow Q_{ij} between nodes i and j is then obtained as:

$$Q_{ij} = C_{ij}(P_j - P_i) \quad (7.5)$$

The wall shear stress in segment ij is then given as (adapting Equation 7.3):

$$\tau = \eta \left. \frac{dv}{dx} \right|_{x=0} = \eta \frac{4v_{max}}{d} \quad (7.6)$$

Since in Poiseuille flow $v_{max} = 2\bar{v}$, and \bar{v} is defined as the volumetric flow divided by the vessel cross-section, one obtains:

$$\tau_{ij} = \frac{32\eta Q_{ij}}{\pi d_{ij}^3} \quad (7.7)$$

When the capillary lattice is in its initial state, the shear stresses τ_{ij} are calculated and assumed to represent the homeostatic state of each vessel segment ij . Subsequently, a perturbation is introduced. In this model, the perturbation was chosen to be a diameter change in one or more of the vessels³. The new shear stresses are calculated, and “eligible” vessel diameters are modified according to a shear stress remodeling rule (see Equation 7.8 below). A capillary can be “eligible” for remodeling only if it is directly connected to a previously modified vessel.

At the heart of the model is a time-dependent shear stress remodeling rule. Looking at a single vessel, the homeostatic shear stress level will be designated as $\tau(0)$. The time-dependent diameter $d(t)$ of the vessel is assumed to obey the difference equation:

$$\frac{\Delta d}{\Delta t} = sd(t) \frac{\tau(t) - \tau(0)}{\tau(0)} \quad (7.8)$$

where s is a parameter representing the sensitivity of relative diameter changes to relative shear stress changes. Equation 7.8 simply states that the relative rate of diameter change is directly proportional to the relative deviation from the homeostatic shear stress level. At each time step Δt , the shear stress is calculated for all vessels in the network, and the diameter change Δd is calculated for each “eligible” vessel. The process progresses in time until all “eligible” vessel diameters reach a steady state value. If the steady state diameter drops below $0.1d(0)$, it is set to zero⁴. Depending on the specific capillary network, a new generation of “eligible” vessels may be defined and the whole remodeling process repeated. In all simulations input pressure was fixed at $P_{input} = 1$ and output pressure was fixed at $P_{output} = 0$ (it was assumed that the system is linear in ΔP). In order to simplify calculations the fixed vessel length was set at $L = \pi/128\eta$ in the appropriate units without loss of generality. Initial capillary diameters were chosen as $d(0) = 1$, unless otherwise noted. To avoid numerical instabilities, the time step Δt was chosen small enough to obtain a “smooth” response. The simulations were implemented using the MATLAB matrix manipulation software. The model routines are listed in section A.8.

³ Any other perturbation which induces asymmetric shear stress changes would be adequate. Such perturbations include length change and pressure or flow changes (if the feeder vessels are not identical).

⁴ A diameter drop to $0.1d(0)$ represents a 10000-fold decrease in conductance. For all effective purposes, there will be no flow through this capillary, and it can be assumed resorbed.

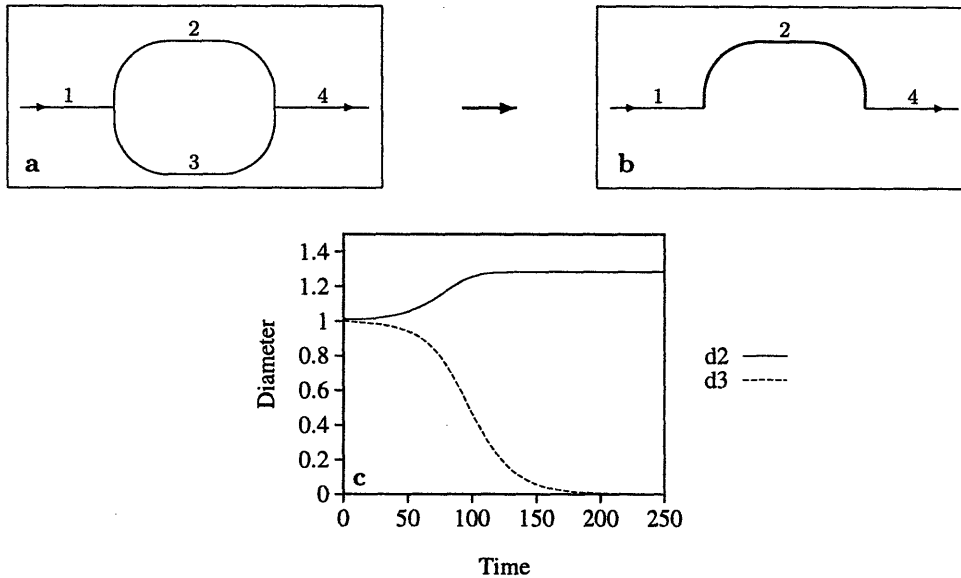


Figure 7-1: Self-loop resorption: (a) The initial self-loop with all diameters being unity; (b) The remodeled structure, after the diameter of vessel 2 was initially perturbed to 1.01, shows that vessel 3 has been resorbed; (c) The time course of the diameter changes. Note that d_2 reaches a steady state before d_3 because when d_3 is small enough it no longer has a significant effect on the flow behavior of the structure. The sensitivity parameter was $s = 0.05$ in this simulation.

7.3 Model Results

In the following sections, I will present several examples showing that this arterIALIZATION model produces the desired results. I will start with the simplest example — a self-loop (a loop with 2 nodes on its perimeter). I will then go on to a loop with 3 nodes on its perimeter. Subsequently, I will explore the model on a capillary lattice. I will show that in all cases selective vessel resorption occurs. This resorption remodels a mesh into a tree-like structure.

7.3.1 Self-Loop Resorption

A self-loop, the simplest of all vascular loop structures, is shown in Figure 7-1a. Such a loop has only two nodes on its perimeter. The loop shown in Figure 7-1a has an input vessel (vessel 1), an output vessel (vessel 4) and two loop vessels (vessels 2 and 3). All vessels start off with a unity diameter, and only vessels 2 and 3 are allowed to remodel. Figure 7-1b shows the resulting vasculature after vessel 2 is perturbed and its diameter increased to 1.01. The time course of the diameter changes of vessels 2 and 3 is shown in Figure 7-1c. A similar result is obtained if vessel 3 is the one perturbed and its diameter initially decreased.

Self-loop resorption is not a purely theoretical exercise. Self-loops occur occasionally in vasculature. Furthermore, self-loop resorption may be a key process in the formation of rare tree-like capillary networks seen in some marsupials [89].

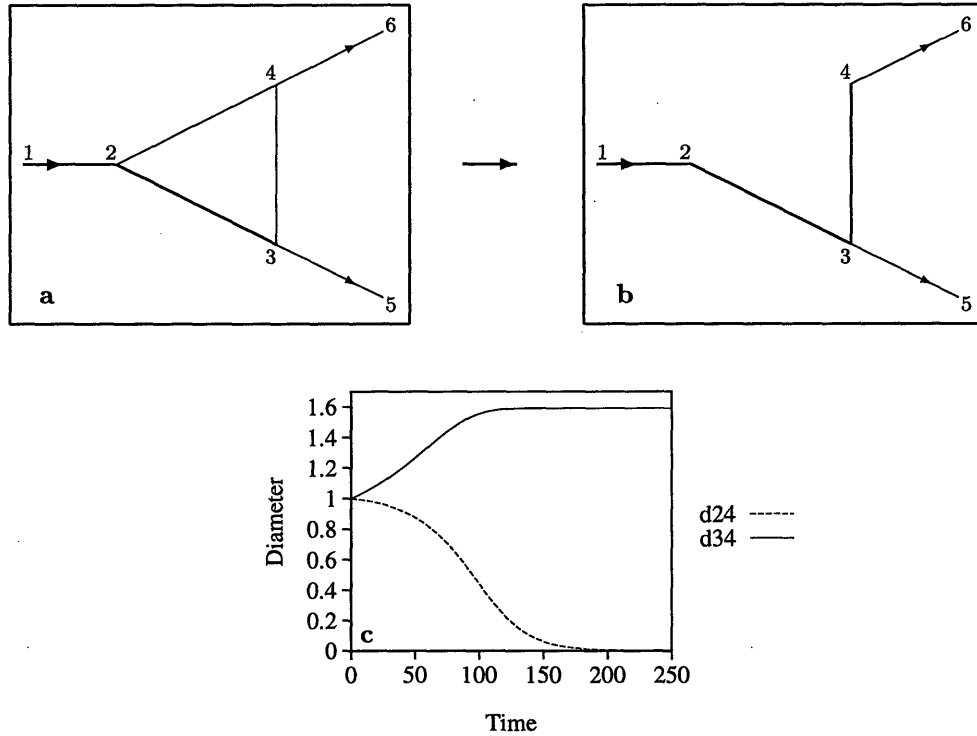


Figure 7-2: Complex loop resorption: (a) The initial structure with $d_{12} = 1.50$, $d_{23} = 1.30$, and all other diameters being unity; (b) The remodeled structure, after d_{23} was initially perturbed to 1.33, shows that vessel 24 has been resorbed; (c) The time course of the diameter changes. The sensitivity parameter was $s = 0.05$ in this simulation.

7.3.2 Complex Loop Resorption

Figure 7-2a shows a loop with three nodes on its perimeter (called a “complex” loop), representing a typical situation during the arterIALIZATION process. Segments 12 and 23 are already arterIALIZED. For the arterIALIZATION to proceed, either capillary 24 or capillary 34 has to be resorbed. The perturbation in this case is an increase in the diameter of arteriole 23 (from 1.30 to 1.33). Only capillaries 24 and 34 are allowed to remodel. The input and output pressures were fixed so $P_1 = 1$ and $P_5 = P_6 = 0$. Figure 7-2b shows the resulting vasculature after vessel diameters d_{24} and d_{34} reach a steady state. The time course of the diameter changes is shown in Figure 7-2c.

The choice of the initial perturbation is important in determining which capillary is resorbed. In the network depicted in Figure 7-2a, a perturbation that slightly increases the diameter of capillary 24 would result in the resorption of capillary 34. In general, however, the key observation is that in this model a small perturbation tends to be amplified, resulting in the resorption of vessels. The choice of sensitivity parameter s was observed to affect only the rate at which the vessels reach their steady-state diameters.

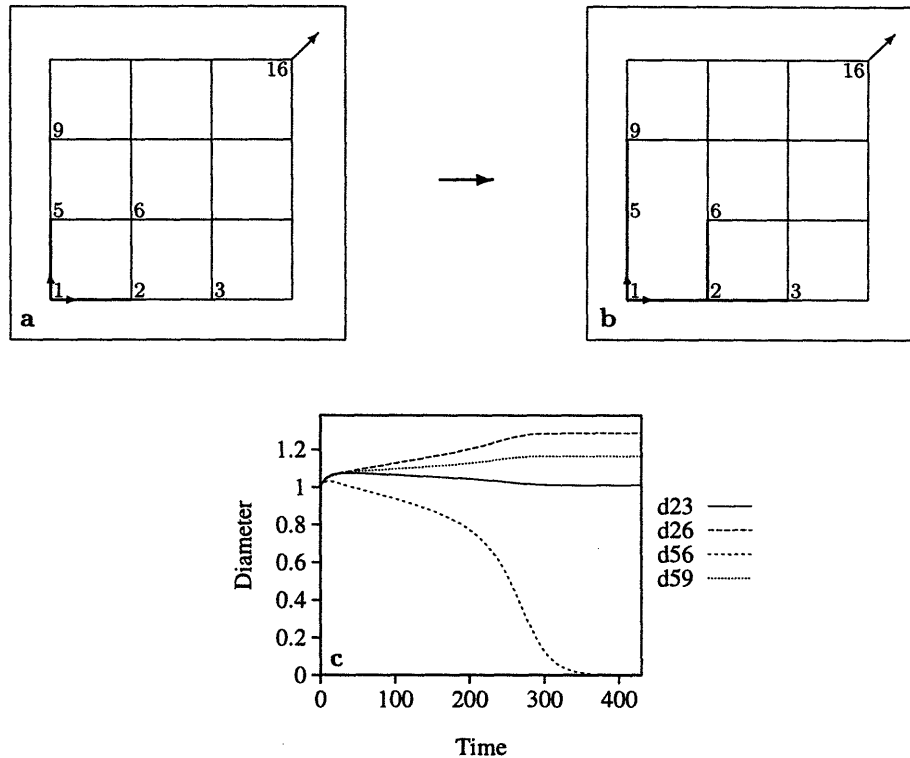


Figure 7-3: Loop resorption on a 3×3 square lattice: (a) The initial lattice with all diameters being unity except $d_{12} = 1.21$ and $d_{15} = 1.19$; (b) The remodeled structure, showing that vessel 56 has been resorbed; (c) The time course of the diameter changes. The sensitivity parameter was $s = 0.05$ in this simulation.

7.3.3 Resorption on a Lattice

In order to assess whether the proposed model yields the desired results in a network consisting of multiple loops, simulations were performed on a square capillary lattice. The input was selected at the lower left corner and output at the upper right corner. In these simulations, the perturbation used was an asymmetrical increase in the diameters of the two vessels connected to the lower left corner (node 1) to 1.21 and 1.19.

Figure 7-3 presents the results obtained on a lattice of 3×3 segments, where remodeling was allowed for one generation. The input and output pressures were fixed so $P_1 = 1$ and $P_{16} = 0$. All vessels directly connected to the perturbed vessels were allowed to remodel (i.e., capillaries 23,26,56,59). Clearly, for a tree structure to develop, either capillary 26 or capillary 56 must be resorbed. Figure 7-3b shows the resulting vasculature after vessel diameters reached a steady state. The time course of the diameter changes is shown in Figure 7-3c. As seen, vessel 56 is resorbed, and the tree structure gains another generation.

Figure 7-4 presents the results obtained on a lattice of 5×5 segments, where remodeling was performed for three generations. The input and output pressures were fixed so $P_1 = 1$ and $P_{36} = 0$. In each generation, only capillaries directly connected to previously remodeled vessels were allowed

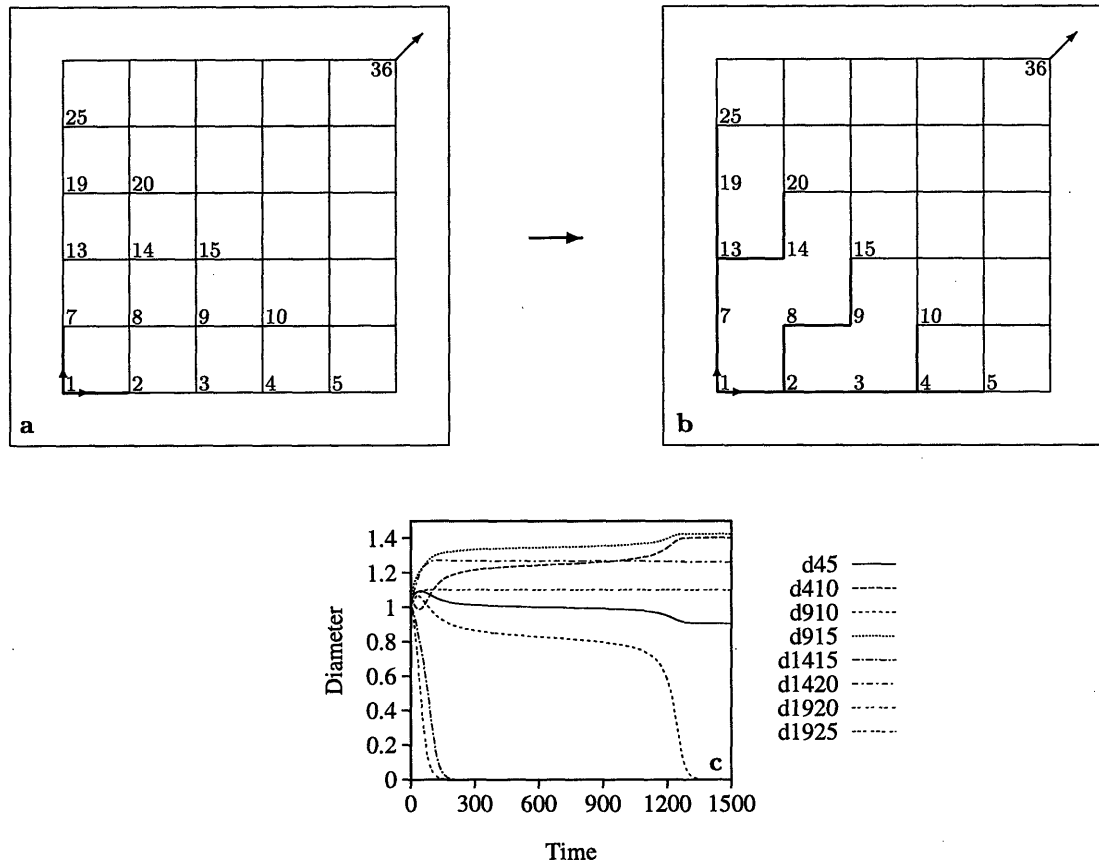


Figure 7-4: Three generations of remodeling on a 5×5 square lattice: (a) The initial lattice with all diameters being unity except $d_{12} = 1.21$ and $d_{17} = 1.19$; (b) The remodeled structure, after three generations of remodeling showing that several vessels have been resorbed; (c) The time course of the diameter changes of the third generation. The sensitivity parameter was $s = 0.05$ in this simulation.

to remodel. Before the third generation remodels, nodes 10, 15, and 20 each have two inflow vessels and two outflow vessels. In order for the tree structure to continue into its third generation, one of the inflow vessels into each of these nodes has to be resorbed. Figure 7-4b shows the resulting vasculature after the third generation vessel diameters reach a steady state. The time course of the diameter changes during the third generation remodeling is shown in Figure 7-4c. It is clear that only those vessels which were superfluous for the formation a tree-like topology were resorbed. It is also important to note that the time needed to reach a steady state in the third generation is approximately 4 times longer than the time needed to reach a steady state in the first generation (compare Figure 7-4c with Figure 7-3c — the different lattice size has negligible effect on first generation remodeling time).

Similar resorption patterns were obtained when the model was implemented on a hexagonal lattice. While a hexagonal lattice does not seem to differ from a square lattice in the potential of certain capillary segments to be resorbed, it seems to be less sensitive to small perturbations to the

symmetry of the lattice. For example, a perturbation of feeder vessel diameters to 1.19 and 1.21 (as in the square lattice case) could not elicit a resorption response. However, a perturbation of feeder vessel diameters to 1.01 and 1.21 elicited a multi-generation resorption of vessels (on a hexagonal lattice of 4×4 hexagons). Since a hexagonal lattice is probably more representative of the connectivity properties of real capillary beds, the above observation insinuates that the connectivity properties of the whole network may temper the divergent nature of stress-induced remodeling.

7.4 Model Evaluation

The results from the simple arterialization model described above contain two salient elements. First, they show that a shear-stress based remodeling rule can result in vessel resorption (and vessel enlargement). Second, they show that this resorption is selective in the sense that only vessels which form connections that are superfluous for tree topology are resorbed. Selective vessel resorption is a key element which must accompany any Laplacian remodeling process in order for the arterial network to achieve a tree structure. This model assumed an “eligibility” criterion, which stated that only vessels connected to previously modified vessels could be remodeled. In real life, vessel “eligibility” could possibly be established by the Laplacian field itself. For example, if a large pressure gradient in a vessel was to cause the smooth muscle cells on the vessel to proliferate and migrate, then arterial growth would occur mostly at the terminal arteriole level.

A model which combines Laplacian growth and stress-based remodeling is easy to conceptualize. In essence, the previous model needs to be implemented on a larger lattice and the eligibility criterion made dependent on the Laplacian field gradient. A larger lattice is needed for two reasons. First, it is impossible to accurately simulate Laplacian growth on a 5×5 lattice. Second, on a 5×5 lattice the total length of all arterial segments is comparable to the total length of all capillary segments. While this situation may be appropriate in simulations of the local mechanism of stress-based remodeling, it is inappropriate in simulations of the global behavior of gradient-sensitive remodeling. This is due to the fact that in real life, the total length of arteries is small compared to the total length of capillary segments. Since capillaries form a mesh and arteries form a tree, the pressure behavior of the capillary bed will be relatively unaffected by upstream changes (the effects of such changes will be felt mostly in the terminal branches of the arterial tree). A situation in which total artery length is small compared to total capillary length can only be achieved on a large lattice, where the remodeling of a few capillaries will not drastically alter the properties of the capillary bed as a whole. Unfortunately, such a large lattice (at least 500×500) requires prohibitive amounts of computing time. At each remodeling generation, at least several hundred time steps are required to achieve a steady-state. At each time step, the flows and pressures must be calculated in the whole network. A 500×500 lattice would have $2.5 \cdot 10^5$ nodes, necessitating the simultaneous solution of this number

of equations (for pressures and flows) *at each time step*. This computation requirement was beyond the resources available for this research. It will be left, sadly, for some unspecified future time.

When a simulation on a larger lattice is conducted, it will also be able to address another issue which the model raises. Some readers may find it troublesome that the vascular system in this model bears the inherent instabilities shown in section 7.3. If a small perturbation can cause profound changes in a vascular network, then the network will fail to provide a stable blood supply to the tissue. This problem is partly addressed by the “eligibility” criterion, which restricts the number of vessels that can be remodeled at a given time. In addition, simulations on square and hexagonal lattices point to a *global* effect which may act to stabilize the *local* instabilities introduced by stress-based remodeling. In subsection 7.3.3 it was observed that as the number of vessels that are allowed to remodel simultaneously increases, the remodeling process takes significantly longer to reach a steady state. Furthermore, it was observed, that a hexagonal lattice was less sensitive to small initial perturbations than a square lattice. Experimental evidence of integration of biological signals by capillary networks [125] may suggest that in a large capillary network multiple perturbations are needed to induce arteriolar response. These observations may lead one to hypothesize the existence of a global stabilizing effect dependent on network size and connectivity. However, a solid confirmation of this effect can only be performed with large lattice simulations.

7.5 Venous Network Formation

The model discussed in previous sections explicitly assumed that the remodeling was occurring from the inflow direction, thus simulating the process of arterialization. There is no mathematical obstacle to extending this sort of remodeling to the outflow side of the network as well, since the mass conservation equations ($\sum_j Q_{ij} = 0$ at each node i) involved in solving for the flow (and hence the shear stress) hold true if the direction of flow is reversed. Thus, one may argue that a branching venous network may form by the same stress-dependent mechanism.

While capillary resorption leading to the formation of post-capillary venules may occur by a mechanism similar to that leading to the formation of terminal arterioles, the source of the “eligibility” criterion in this case is less obvious. If the “eligibility” criterion is gradient-sensitivity, as postulated in the arterial case, then the source of the Laplacian field is more obscure in the venous case, because the pressure gradients throughout the venous side are relatively low. A possible solution to this problem lies in the observation that the histological difference between capillary and venule is less pronounced than the difference between capillary and arteriole [63], although, on average, venules have larger lumen diameters than arterioles. This may lead us to suspect that resorption of capillaries leading to the formation of venules may have a passive component to it. Such a component would manifest itself in the enlargement of diameter in response to increased

flow without an active mechanism (e.g., stress-based) for vessel resorption. In this scenario, some vessels would be resorbed when a neighboring vessel becomes large enough to occlude them or to draw enough flow away from them (by virtue of increased conductance) so as to collapse them. Due to the limited and controversial knowledge about the mechanical nature of vessel collapse and occlusion, this hypothesis should be regarded as highly speculative. Unfortunately, there have been no comprehensive studies of the dynamics of concomitant arterial and venous network formation. Such a study is necessary to determine whether the same time constants are involved and whether the same resorption patterns are observed. Until then, the model proposed in this chapter can apply to both arterial and venous network formation.

Chapter 8

Transport Implications

The transport of diffusible substances in tumors is a key process in the growth and treatment of solid tumors [61, 62]. For example, adequate oxygen supply is critical for tumor growth but also for successful radiation therapy. The scale-invariant behavior of vascular networks uncovered in Chapter 4 leads to important insights about the transport characteristics of tumors. It will be shown that by using percolation-like scaling as a paradigm for tumor vasculature, important experimental observations can now be explained.

Historically, most transport models have relied on drastic simplifications of vascular architecture. The most commonly used model, the Krogh cylinder, is based on the assumption of uniformly spaced straight parallel vessels [104]. The Krogh cylinder model is appropriate in the case of a vasculature which displays compact scaling behavior, such as the normal capillary bed. Indeed, one of this model's most profound impacts has been in the study of oxygen exchange in skeletal muscle [104], where capillaries can be accurately approximated to be parallel and arranged on a two-dimensional hexagonal lattice when viewed in cross section [11]. However, in this study it has already been shown that tumor vasculature does not display compact scaling but rather percolation-like scaling (section 4.2). Tumors are known for tortuous vessels and for avascular areas of many different sizes [1, 60, 68, 76], thus violating the assumptions necessary for the application of the Krogh cylinder model. Given the unavailability of a general vascular architecture model in tumors, there have been some attempts to quantify the transport characteristics of tumors by using reconstructions of small regions of tumor vasculature [114]. While these studies were important in demonstrating that the Krogh cylinder model was indeed inappropriate for quantifying the transport characteristics of tumors, their conclusions could not be extended to other tumor networks because the studies did not include a quantitative model of vascular architecture. By using the findings of this research, I will show that a general paradigm can be developed for assessing the transport behavior of scale-invariant vascular networks.

8.1 Geometric Resistance

The percolation-like ($d_f \approx 1.9$) behavior of tumor vasculature helps explain a long-standing paradox regarding the geometric resistance of tumors. Experimentally, it has been observed that tumors display elevated geometric resistance to blood flow when compared to normal tissues of similar weight [115]. However, it has also been observed that tumor vessels increase in diameter as the tumor grows. The mean diameter d of tumor vessels can often be more than 100% larger than that of normal vessels [52]. Since the geometric resistance is proportional to d^{-4} , we can see that, *ceteris paribus*, the geometric resistance of tumors would have to decrease in comparison to normal tissue. One can argue that in tumors one usually sees a decrease in the vascular density when compared to normal tissue. However, if one assumes that the vascular density is uniformly decreased in the tumor, then in order to counteract a 100% increase in vessel diameter to obtain elevated geometric resistance, the vascular density would have to decrease by a factor larger than 16. Published figures about vascular density in tumors show that it is typically 2-4 times less than normal tissue [25, 78]. Therefore, the source of the elevated geometric resistance remained shrouded in mystery.

The observed scale-invariant properties of tumor vasculature undermine the assumption that vascular density is uniformly reduced in tumors. Since tumors behave like percolation clusters, the large body of work dealing with the electrical resistance of random resistor networks [127] can be applied to explain the aforementioned paradox. In general, the resistance z_0 of a percolation cluster above the percolation threshold is known to obey the power law:

$$z_0 \propto (p - p_c)^{-\mu} \quad (8.1)$$

where p represents the occupancy level, p_c is the percolation threshold, and μ is a positive number. In two dimensions $\mu \approx 1.3$ [127]. We see that close to the percolation threshold ($d_f \approx 1.9$) the resistance diverges, consistent with the observation for tumor networks.

Given the similarity between tumor networks and percolation clusters, one can also cite two intuitive reasons for the elevated resistance in tumor networks. First, the connectivity properties of percolation networks are such that there may be a few flow paths that will carry a disproportionately large part of the flow (technically known as “singly connected bonds” [126]). In contrast, in a compact network the symmetry of the structure assures a fairly homogeneous flow distribution. Second, the flow paths in tumor networks tend, on average, to be longer than flow paths in normal networks, as shown by the elevated minimum path dimension d_{min} in tumor networks (Section 4.2). Since the geometric resistance is directly proportional to the length of the flow path, a tumor vessel with elevated d_{min} will have higher geometric resistance compared to a normal vessel, provided that both vessels are of equal diameter and connect equally distant points.

8.2 Scaling of Avascular Regions

The percolation-like ($d_f \approx 1.9$) structure of tumor vasculature has important implications for transport of diffusible substances in tumors. The number of vascular regions N_{vasc} of length scale L scales as:

$$N_{vasc} = \left(\frac{L_0}{L}\right)^{d_f} \quad (8.2)$$

where L_0 is the upper boundary of the fractal scaling range. The number of all regions (both vascular and avascular) N_{all} of length scale L scales as:

$$N_{all} = \left(\frac{L_0}{L}\right)^D \quad (8.3)$$

where D is the embedding Euclidean dimension ($D = 2$ in our case). Therefore, the fraction of tissue f_{avasc} consisting of avascular areas of length scale L scales as:

$$f_{avasc} \equiv \frac{N_{all} - N_{vasc}}{N_{all}} = 1 - \left(\frac{L_0}{L}\right)^{d_f - D} \quad (8.4)$$

This implies that for structures with $d_f \approx 1.9$ and $D = 2$ there exist a few large avascular areas and many smaller avascular areas. The number of cells in the few large avascular areas is not negligible, however. For the observed value of $L_0 \approx 900 \mu\text{m}$ and a single-cell length scale of $10 \mu\text{m}$, it can be calculated that 39% of all cells will lie in avascular areas of length scale $L > 200 \mu\text{m}$. In a three-dimensional percolation-like structure ($d_f \approx 2.5$ and $D = 3$), 59% of the cells lie in avascular areas of the same length scale. These percentage figures should not be regarded as more than order-of-magnitude estimates, but they point to the observation that the relatively scarce but large avascular areas have the most clinical significance, since they are the areas most prone to resist drug treatment or to be hypoxic and resist radiation treatment.

The relationship stated in Equation 8.4 can be demonstrated by measuring the distance of each point in the tissue to the nearest vessel. Figure 8-1 shows the cumulative distribution of the fraction of tissue at or above a given distance from the nearest vessel (the fraction at or above 1 distance unit (approximately $6 \mu\text{m}$) was normalized to be 1.0). The distribution is shown for three representative normal subcutaneous striated muscle capillary networks and three representative LS174T tumor vascular networks. It is evident that the distance distribution in tumors has a much longer tail than that in normal tissue. The long tail reflects the existence of the large avascular areas in tumors. The differences among tumor distributions reflect the variability in size and number of the largest avascular areas. The normal vasculature distributions, however, show little variability. This is due to the relatively uniform intervessel spacing observed in normal tissue. The distributions shown in Figure 8-1 are very similar to those derived from invasion percolation clusters [7].

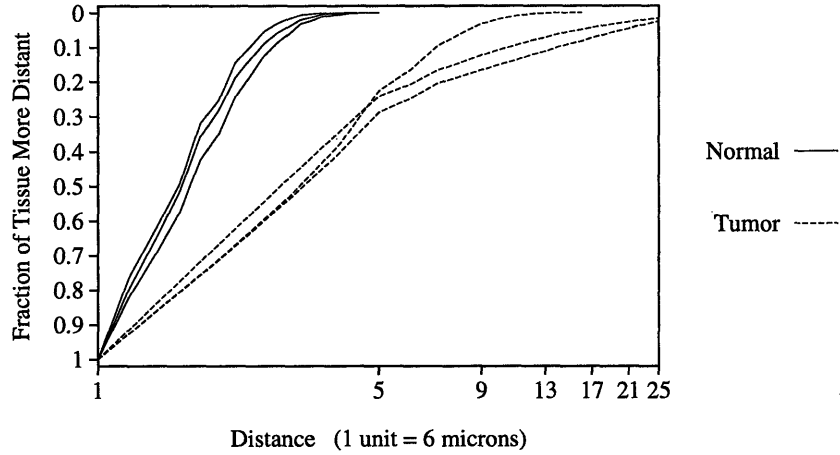


Figure 8-1: Fraction of tissue more distant from nearest vessel as measured from images of normal subcutaneous muscle capillary networks and LS174T tumor networks. The long tail of the tumor distributions reflects the existence of large avascular regions in tumor tissue. The variability in tumor distributions reflects the variability in the size and number of the largest avascular spaces. Note that the horizontal axis is logarithmic.

8.3 Oxygen Transport

Examination of oxygen transport is a useful paradigm in explaining the general transport properties of diffusible substances in tumors. Like many other nutrients or drugs, oxygen is transported via convection in blood and then diffusion from the blood into the extravascular space. Experimentally, tumors are known to display large variations in oxygenation measurements [130]. Hypoxic and anoxic regions are frequently found in tumors [64], but rarely in normal tissue.

The spacing between vessels is an important determinant of oxygen levels in tissue. Under steady diffusion in one dimension, the maximum distance d_{max} that oxygen can diffuse from blood vessels, assuming uniform tissue oxygen solubility α and uniform tissue oxygen consumption M_0 , is given by [114]:

$$d_{max} = \sqrt{\frac{2D\alpha P_v}{M_0}} \quad (8.5)$$

where D is the diffusivity and P_v is the partial oxygen pressure in the vessel. Experimentally derived values for $D\alpha$, P_v and M_0 in tumors show that d_{max} can range from 41 μm to 183 μm [114]. In normal tissue, the avascular spaces are relatively uniform in size and the intervessel distances are well below $2d_{max}$. In tumors, however, the large avascular spaces discussed in section 8.2 can lead to the creation of hypoxic regions.

The effects of the percolation-like nature of tumor networks on oxygen delivery are not limited to the creation of hypoxic regions in the large avascular spaces. The increased resistance of tumor networks reduces flow to the tumor as a whole, thus aggravating hypoxic conditions. The existence

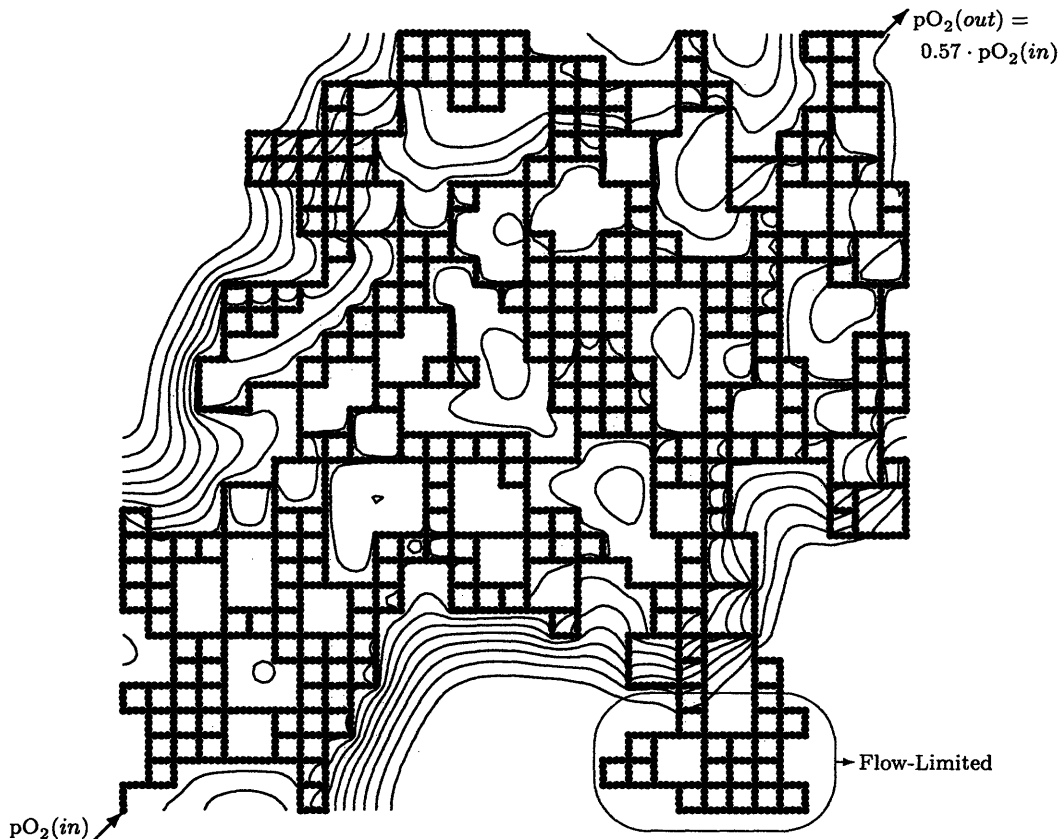


Figure 8-2: Oxygenation contours on a percolation network. Contours reflect 10% increments in oxygen concentration. The above network was generated on a 32×32 lattice with an invasion percolation algorithm, which continued until the backbone had a 60% occupancy level. The input was chosen at the lower right corner with 100% oxygen saturation. The output was chosen at the upper left and the flow rate adjusted so the partial oxygen pressure at the exit would be 57% of the inlet oxygen pressure. A locally flow-limited hypoxic region is evident in the lower right.

of a few flow paths which carry a disproportionately large share of the flow in a percolation network (the “singly connected bonds”) makes oxygen delivery by such networks much more sensitive to intermittent flow cessation (e.g., by vessel collapse) in random vessels, whereas normal capillary networks are relatively insensitive to flow cessation in a few random capillaries [56]. Furthermore, the flow heterogeneity in a percolation network can result in hypoxic regions due to local flow limitations, even when those regions are fully vascularized.

The effects of percolation-like scaling on oxygen delivery were quantitatively examined in a recent study [7] based on the work described in this thesis. In that study an invasion percolation model was used to generate two-dimensional networks on a square lattice. Using finite difference techniques, the oxygen convection and diffusion equations were solved for the oxygen concentrations throughout the lattice. The results show that even when oxygen concentration at the network outlet is maintained at relatively high levels, there will still be hypoxic regions due to the effects described above. This can be seen in Figure 8-2 adapted from Reference [7]. The outlet partial oxygen pressure

$pO_2(out)$ was set at $0.57 \cdot pO_2(in)$ by maintaining a high enough inflow rate. Hypoxic regions are evident in the large avascular areas, yet there is also a hypoxic region that is well-vascularized but flow-limited. In the aforementioned study [7] many additional networks were generated and oxygenation levels measured in the model networks were used to generate cumulative oxygenation histograms. These histograms bore a striking similarity to experimentally obtained oxygenation histograms. The small qualitative differences that existed between the in vivo measurements and the model's results could be attributed to the neglect of three-dimensional effects [7].

8.4 Clinical Implications

The inherent limitations to oxygen transport in tumor tissues having percolation-like vascular networks can be generalized to include most other substances that are delivered to target cells by similar convective and diffusive processes. Such substances include both nutrients (e.g., glucose) and therapeutic agents (e.g., drugs or antibodies). As demonstrated in Figure 8-2, even when the tumor as a whole does not deplete the blood of a particular diffusible substance, there will still be regions in the tumor, both vascular and avascular, that will have very low levels of the particular substance. The clinical implication of this observation is that interventions designed to enhance blood flow in tumors may be inadequate to assure delivery of drugs to all tumor cells. In order to assure better delivery of drugs to tumor tissue an intervention that promotes the formation of a more compact and uniform vascular network is necessary. However, the formation of compact vascular networks in tumors may have the detrimental effect of speeding up tumor growth by providing a more uniform supply of nutrients to tumor cells.

Another important implication lies in the potential efficacy of anti-angiogenic interventions. Such interventions are targeted against tumor vessels and are intended to retard tumor growth by cutting off the blood supply to tumor cells. Anti-angiogenic interventions are often combined with standard chemotherapeutic regimens. The effects of such treatments can depend greatly on the manner in which blood vessels are affected. If vessels are resorbed in a random manner, then it is conceivable that anti-angiogenic treatment may push the vascular network closer to the percolation threshold or even below it, thus depriving more tumor tissue of nutrient supply but also reducing the efficacy of any drugs. If vessels, however, are resorbed in manner which creates a sparser yet more compact network, both nutrient supply and drug delivery to tumor cells may become more uniform.

While the conclusions regarding oxygen transport can be readily applied to the transport of most diffusible substances, they may not be valid for heat transfer. Both experimental [74] and theoretical [4] studies have shown that vessels with diameters less than $100 \mu m$ are insignificant for heat transfer. In the tissues studied in my experiments virtually no vessels of diameters larger than $100 \mu m$ were present. Such vessels can be seen in tissue samples whose dimensions are much

larger than those studied. This implies that in the case of tumor specimens of millimetric size, the heat transfer properties are determined largely by the vasculature of the surrounding tissue and not by the vasculature of the tumor itself. Furthermore, the tissue length scales at which thermally significant vessels are found are most likely above the upper boundary of the fractal range observed in this study (length scales larger than 1 mm). At these length scales the tumor vasculature may no longer display percolation-like scaling (see section 4.3).

Chapter 9

Future Directions

The results described in the preceding chapters can be further explored and developed in the future. The main directions for future research involve three areas:

- Extension of experiments to three dimensions.
- Experiments directed towards refinement of shear-stress based artery-vein growth model.
- Incorporation of the scale-invariant properties of vascular networks into transport models.

9.1 Extension to Three Dimensions

The measurements of fractal dimensions reported in this thesis were performed in a unique quasi-two-dimensional transparent preparation of transplanted tumor cells. Most of the studies of tumor vasculature to date have been performed in transplanted tumors in various specialized preparations. However, it has been suggested that the vasculature of transplanted tumors may show some differences when compared to the vasculature of the primary tumor [31], although the differences reported are mostly physiological and not morphological. Clearly, it would be ideal if the three-dimensional vasculature of a primary lesion could be imaged in situ.

Virtually all possible three-dimensional imaging methods were explored as candidates for imaging vasculature. The requirements for images to be suitable for fractal dimension measurements are those of resolution. The resolution must be high enough that individual vessels could be identified, but low enough to assure that enough vessels will be included in each image so that fractal dimension measurements will be reliable and that a large enough number¹ of vascular networks could be processed in a reasonable time.

¹In this study fractal dimensions were measured in a total of **106** vascular networks.

One tried method for the imaging of three-dimensional vasculature is that of quantitative reconstruction using serial sections [17]. However, this method has two shortcomings. First, preparing and imaging the serial sections is an extremely laborious process making the imaging of large number of vascular networks practically impossible. Second, this method is destructive, making repeated measurements of the same network impossible.

Another commonly used method for visualization of vessels in their three-dimensional arrangement is that of corrosion casting [116]. Using this technique, a cast is made by injecting a compound into the vessels, the compound subsequently hardens, and the tissue is digested chemically. Traditionally, these casts have been observed using electron microscopy. However, the electron microscopic approach does not offer a way to image the whole three-dimensional structure, but merely to observe limited portions of it. In order to use the corrosion casts for obtaining a three-dimensional vascular image, a truly three-dimensional technique should be used to image them. However, no such technique exists for direct three-dimensional image acquisition (the resolution of NMR microscopy is not sufficient).

Laser scanning confocal microscopy (LSCM) has been used to image vessels at varying focal depths [92]. However, limits on the total thickness and on the minimum focal slice size under the relatively low magnifications necessary for imaging a large enough number of vessels make this method, too, impractical for imaging three-dimensional vascular networks for the purpose of measuring fractal dimensions.

In summary, at this stage no currently known method can produce three-dimensional vascular images of the desired quality and quantity necessary for fractal dimension measurements. These measurements should be performed when an acceptable imaging technique is available.

Extending Computer Algorithms to 3-D

The computer algorithms used to measure fractal dimensions can be trivially extended to three dimensions. The only practical limitation is that of computing time. In order to show that the 2-dimensional tumor vascular growth model (see Chapter 6) can be extended to three dimensions, the source code was modified to incorporate a third spatial dimension (see section A.7). The model was applied to a $32 \times 32 \times 32$ square lattice, with a local amplification factor of $F = 3$, and with a series of accessibility parameters T ranging from 30% to 100% (the percolation threshold in three dimension is $p = 0.3116$ [127]). For each T value, $n = 10$ runs were performed. The relatively small lattice size and sample size were chosen because of computing time limitations. The resulting fractal dimensions are graphed in Figure 9-1.

Figure 9-1 shows that, as in the 2-dimensional case, there is a transition from a non-space-filling fractal vasculature to a space-filling compact vasculature. Furthermore, structures with fractal dimension similar to a three-dimensional critical percolation cluster ($d_f \approx 2.5$ [127]) occur for $T \sim 0.5$,

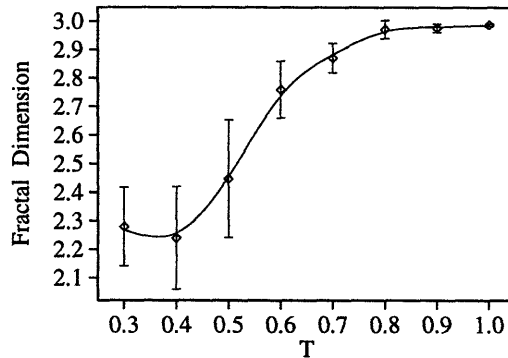


Figure 9-1: Fractal dimensions in 3-D growth model. The tumor vasculature growth model from Chapter 6 was modified to include a third spatial dimension. The model was applied to a $32 \times 32 \times 32$ square lattice, with a local amplification factor of $F = 3$, and accessibility parameter T ranging from 0.3 to 1.0. The transition from a non-space-filling structure to a space-filling structure is evident. The relatively large error bars are due to the small sample size ($n = 10$ in the 3-dimensional runs vs. $n = 100$ in the 2-dimensional runs).

higher than the percolation threshold ($p = 0.3116$) for a three-dimensional square lattice. This behavior is qualitatively similar to the 2-dimensional case. It is due to the fact that not all perimeter sites are explored at each growth cycle because of the finite local amplification factor F (see section 6.5).

In order to further verify the 3-dimensional model, the model was run with parameters corresponding to diffusion-limited aggregation ($F = 0$ and $T = 1.0$) on the same 3-dimensional square lattice. The mean fractal dimension ($n = 10$) calculated was $d_f = 2.49 \pm 0.09$, in agreement with the reported value of $d_f \approx 2.5$ for three-dimensional DLA [90].

The availability of a robust 3-dimensional vascular growth model should further encourage the development of an experimental design to facilitate the measurement of fractal dimensions of three-dimensional vascular networks in tumors in situ.

9.2 Artery and Vein Formation Experiments

The shear-stress based model for vessel growth and resorption presented in Chapter 7 offers a good argument that shear stress variations may be important in the process of artery and vein formation. A large body of existing evidence shows that shear stress variations induce a variety of changes at the molecular and cellular levels in endothelial cells [55, 98, 102, 122]. Furthermore, studies at the network level have suggested that states of altered shear stress are associated with vessel rarefaction [109, 120]. However, to date there have been virtually no studies following the arterIALIZATION (or vein formation) process at the single vessel and network levels.

Before the artery-vein growth model can be expanded and improved, several key experimental observations must be made. First, the process of artery and vein formation should be observed *in vivo*, to establish the time course and the spatial progression of capillary enlargement and resorption. Second, the process of arterialization should be correlated with the hemodynamic behavior preceding it or occurring concomitantly with it. Then experiments should be performed in which shear stress is modified in the observed vessels and the effects of these changes on the process of arterialization are explored. In addition, the process of vein formation should be observed and compared to the arterialization process.

Even if the experiments verify the model's basic assumptions of shear stress based remodeling, there will still be important questions regarding the nature of the homeostatic shear stress levels. Flow changes (and hence shear stress changes) occur constantly in quiescent vascular networks. Therefore, the homeostatic shear stress level may be some sort of average level sensed by the endothelium. Is the homeostatic shear stress level averaged over time, over space, or both? Are there factors which influence the stability of the homeostatic shear stress level? These questions can only be answered by careful experimentation.

9.3 Scale-Invariant Networks in Transport Models

Modeling vascular networks as scale-invariant structures grown according to a specific statistical growth process can contribute to the understanding and modeling of transport processes in tissue by providing a general paradigm to study the effects of various parameters on transport properties. This is important because in tissues with dramatically heterogeneous hemodynamic and geometric vascular parameters (such as tumors), the study of a particular experimental preparation is of limited use. Thus, an approach, such as the growth of percolation networks, that can statistically reproduce these heterogeneities is of interest.

In Chapter 8 it was shown that the scale-invariant nature of tumor networks helps explain the elevated geometric resistance of these networks, and also predicts the scaling of avascular spaces in tumor tissue. Furthermore, a simple oxygen transport model using a percolation network with a single inlet, a single outlet, and uniform vessel diameters produced results which were in agreement with experimentally observed oxygen transport properties in tumors.

The model presented in Chapter 8 can be further extended in several directions.

- The transport properties of a network can be studied at several stages during its growth. This would help determine if there are particular stages in a network's development during which transport properties are particularly different than other stages.
- Including more than one outlet or inlet. In real networks there is rarely a single outlet or inlet. The effects of multiple inlets or outlets should be determined (e.g., is flow reversal more likely

in one setting or another?).

- Incorporating heterogeneous diameters. In real tumor networks the diameters vary significantly, even along a particular segment. The effect of diameter variability should be explicitly studied.
- Introducing physiologic parameters into the model such as active flow control mechanisms (e.g., vasoconstriction).

By allowing computer simulations of many networks which are different in geometric parameters yet are similarly scale-invariant, the most important determinants of tumor network transport properties may be identified. Such a finding could be important for enhancing drug and nutrient delivery.

Aside from molecular transport, the implications of the scale-invariant nature of vascular networks for heat transfer should also be examined. It is important to examine whether the existence of large avascular spaces in tumors may alter the vessel size which is to be considered as thermally significant. In normal tissue, vessels smaller than $100\mu\text{m}$ in diameter are considered thermally insignificant. Whether this conclusion holds in the case of tumor tissue, where vessel diameter and spacing vary much more than in normal tissue, needs to be explored.

Appendix A

Source Code

Following are listings of the key computer programs written and used in this research. Fractal dimension calculation programs were written using the THINK Pascal programming language (Symantec; Cupertino, CA) and incorporated into the NIH-Image software¹. The modeling program was written using FORTRAN 77. The stress-based remodeling program was written using MATLAB matrix manipulation software.

A.1 External Pascal Routines

The following external Pascal routines are referred to in the Pascal programs:

DisposPtr frees the memory used by a given pointer variable.

GetDateTime retrieves the system time in seconds.

IUTimeString formats the system time for display.

PutMessage displays a message using a note alert [86].

PutChar writes a character to NIH-Image's text buffer.

PutReal writes a real variable to NIH-Image's text buffer.

PutString writes a string to NIH-Image's text buffer.

SaveAsText saves NIH-Image's text buffer to a file, based on the information obtained through the SFPutFile routine.

SelectAll defines the whole image as the region of interest.

¹NIH-Image is a public domain program. The software and all supporting documentation are available by anonymous ftp from [zippy.nimh.nih.gov](ftp://zippy.nimh.nih.gov).

SFPutFile brings up Macintosh's file saving dialog box and obtains the file saving information from the user [86].

ShowMessage displays a string in NIH-Image's Info window.

A.2 Box Counting Algorithm

```

procedure DoBoxDimension;
const
  NUM_BOX_SIZES = 25;
  BOXES_WITH_NO_ITERATIONS = 3;
  INCLUDE_SECONDS = FALSE;
  WIDTH_TOTAL = 10;
  WIDTH_FLOAT = 8;
  MAX_LENGTH = 1024;
type
  ImageType = array[0..MAX_LENGTH, 0..MAX_LENGTH] of Boolean;
  ImageTypePtr = ^ImageType;
var
  imageArray: ImageTypePtr;
  vstart, vend, hstart, hend, width, width1, height, height1, hloc,
  vloc, k, j, i, i9, dbmFirst, dbmLast: integer;
  sizeIndex, e, e1, end1, xs, ys, xMargin, yMargin, nBoxX, nBoxY,
  noIterationsCount, dbcFirst, dbcLast: integer;
  x0, y0, cx, cy, xStart, xEnd, yEnd, maxL, LARGEST_BOX_INDEX,
  FIRST_BOX_INDEX, LAST_BOX_INDEX: integer;
  longtmp1, longtmp2, e2, occBox, minOccBox, configIdx, timeInSeconds,
  dbint, dbdec1, dbdec2, sddbint, sddbdec1, sddbdec2: longint;
  temp1, temp2, xr, yr, dcbmn, sddbcmn: extended;
  sx, sy, st2, db, ss, sxoss, t, intcp, sintcp, sddb,
  chi2, chi2Min, sigdat, dbmax, sddbmax: extended;
  theLine: LineType;
  boxSizes: array[1..NUM_BOX_SIZES] of integer;
  occupiedBoxes: array[1..NUM_BOX_SIZES] of longint;
  lnBoxSizes, lnOccupiedBoxes, localSlope:
  array[1..NUM_BOX_SIZES] of extended;
  smessage, smessage1, timeString, strtemp: Str255;
  where: point;
  reply: SFReply;
  AutoSelectAll: Boolean;
begin
  with info do begin
    if BinaryPic then begin
      TextBufSize := 0;
      boxSizes[1] := 512;
      temp1 := 512.0;
      for k := 2 to NUM_BOX_SIZES do begin
        repeat
          temp2 := 0.793700526 * temp1;
          j := round(temp2);
          temp1 := temp2
        until j <> boxSizes[k - 1];
        boxSizes[k] := j;
      end;

      AutoSelectAll := not RoiShowing;
      if AutoSelectAll then
        SelectAll(false);

      if roiType <> RectRoi then begin
        PutMessage('I can only deal with a rectangular ROI!');

```

```

    exit(DoBoxDimension);
end;

with RoiRect do begin
    hend := right;
    vend := bottom;
    vstart := top;
    hstart := left;
    width := right - left;
    height := bottom - top;
end;
width1 := width - 1;
height1 := height - 1;
if width > height then
    maxL := width
else
    maxL := height;

smessage := concat('Idx', tab, 'Size');
LARGEST_BOX_INDEX := 0;
repeat
    LARGEST_BOX_INDEX := LARGEST_BOX_INDEX + 1;
until boxSizes[LARGEST_BOX_INDEX] < maxL;

imageArray := ImageTypePtr(NewPtr(SizeOf(ImageType)));
if imageArray = nil then begin
    DisposPtr(ptr(imageArray));
    PutMessage('Insufficient memory');
    exit(DoBoxDimension);
end;
if (height > MAX_LENGTH) or (width > MAX_LENGTH) then begin
    longtmp1 := MAX_LENGTH;
    DisposPtr(ptr(imageArray));
    PutMessage(concat('Image width/length must be less than ',
        long2str(longtmp1), ' for dimension calculation!', cr, 'Change
        MAX_LENGTH constant in source code for larger image.));
end;
for vloc := 0 to height1 do begin
    GetLine(hStart, vloc + vstart, width, theLine);
    for hloc := 0 to width1 do begin
        if theLine[hloc] = 0 then
            imageArray^[hloc, vloc] := FALSE
        else
            imageArray^[hloc, vloc] := TRUE;
    end;
end;

for k := LARGEST_BOX_INDEX to NUM_BOX_SIZES do begin
    longtmp1 := k;
    longtmp2 := boxSizes[k];
    if k < 10 then
        smessage := concat(smessage, cr, '0', long2str(longtmp1),
            tab, long2str(longtmp2))
    else
        smessage := concat(smessage, cr, long2str(longtmp1),
            tab, long2str(longtmp2));
end;

smessage := '';
smessage1 := '';

PutString(concat('Number', tab, 'Box Size', tab, 'Occupied Boxes',
    tab, 'ln [Box Size]', tab, 'ln [Occupied Boxes]', tab,
    'Local Slope', cr));

GetDateTime(timeZero);
noIterationsCount := 0;

```

```

for sizeIndex := LARGEST_BOX_INDEX to NUM_BOX_SIZES do begin
  noIterationsCount := noIterationsCount + 1;
  e := boxSizes[sizeIndex];
  e1 := e - 1;
  if noIterationsCount > BOXES_WITH_NO_ITERATIONS then
    end1 := e1
  else
    end1 := 0;
  longtmp1 := end1 + 1;
  e2 := longtmp1 * longtmp1;
  configIdx := 0;
  longtmp1 := width;
  longtmp2 := height;
  minOccBox := longtmp1 * longtmp2;
  for xs := 0 to end1 do begin
    for ys := 0 to end1 do begin
      configIdx := configIdx + 1;

      if CommandPeriod then begin
        beep;
        DisposPtr(ptr(imageArray));
        exit(DoBoxDimension);
      end;

      xMargin := width + xs;
      yMargin := height + ys;
      occBox := 0;

      xr := xMargin / e;
      longtmp1 := trunc(xr);
      temp1 := longtmp1;
      if temp1 = xr then
        nBoxX := longtmp1 - 1
      else
        nBoxX := longtmp1;

      yr := yMargin / e;
      longtmp2 := trunc(yr);
      temp2 := longtmp2;
      if temp2 = yr then
        nBoxY := longtmp2 - 1
      else
        nBoxY := longtmp2;

      for i := 0 to nBoxX do begin
        for j := 0 to nBoxY do begin
          x0 := i * e;
          y0 := j * e;

          cx := x0 - xs;
          if cx < 0 then
            xStart := 0
          else
            xStart := cx;

          cx := x0 - xs + e1;
          if cx > width1 then
            xEnd := width1
          else
            xEnd := cx;

          cy := y0 - ys;
          if cy < 0 then
            yStart := 0
          else
            yStart := cy;

          cy := y0 - ys + e1;

```



```

    if cy > height1 then
        yEnd := height1
    else
        yEnd := cy;

    for vloc := yStart to yEnd do begin
        for hloc := xStart to xEnd do begin
            if imageArray^[hloc, vloc] then begin
                occBox := occBox + 1;
                vloc := yEnd;
                hloc := xEnd;
            end;
        end;
    end;
end;
end;
if occBox < minOccBox then
    minOccBox := occBox;
end;
ShowMessage(concat(smmessage, cr, cr, 'Configuration ',
    long2str(configIdx), ' out of ', long2str(e2),
    cr, 'Minimum occupied boxes: ',
    long2str(minOccBox)));
end;
occupiedBoxes[sizeIndex] := minOccBox;
GetDateTime(timeInSeconds);
timeInSeconds := timeInSeconds - timeZero;
IUTimeString(timeInSeconds, INCLUDE_SECONDS, timeString);
longtmp1 := boxSizes[sizeIndex];
longtmp2 := occupiedBoxes[sizeIndex];
smmessage := concat(smmessage1, cr, long2str(longtmp1), tab,
    long2str(longtmp2));
ShowMessage(concat('Sz', tab, 'occupied', smmessage, cr,
    'Time: ', timeString));
smmessage1 := smmessage;
smmessage := concat(smmessage, cr, 'Time: ', timeString);
lnBoxSizes[sizeIndex] := Ln(boxSizes[sizeIndex]);
lnOccupiedBoxes[sizeIndex] := Ln(occupiedBoxes[sizeIndex]);
end;

for sizeIndex := LARGEST_BOX_INDEX to NUM_BOX_SIZES do begin
    if (sizeIndex > LARGEST_BOX_INDEX + 1) and
        (sizeIndex < NUM_BOX_SIZES - 1) then begin
        sx := 0.0;
        sy := 0.0;
        st2 := 0.0;
        db := 0.0;
        for i9 := sizeIndex - 2 to sizeIndex + 2 do begin
            sx := sx + lnBoxSizes[i9];
            sy := sy + lnOccupiedBoxes[i9];
        end;
        ss := 5.0; {number of points to calculate local slope}
        sxoss := sx / ss;
        for i9 := sizeIndex - 2 to sizeIndex + 2 do begin
            t := lnBoxSizes[i9] - sxoss;
            st2 := st2 + t * t;
            db := db + t * lnOccupiedBoxes[i9];
        end;
        db := 0.0 - db / st2;
        localSlope[sizeIndex] := db;
    end
else
    localSlope[sizeIndex] := 0.0;

    longtmp1 := sizeIndex;
    strtemp := long2str(longtmp1);
    PutString(strtemp);
    PutChar(tab);

```

```

longtmp1 := boxSizes[sizeIndex];
strtemp := long2str(longtmp1);
PutString(strtemp);
PutChar(tab);
longtmp2 := occupiedBoxes[sizeIndex];
strtemp := long2str(longtmp2);
PutString(strtemp);
PutChar(tab);
PutReal(lnBoxSizes[sizeIndex], WIDTH_TOTAL, WIDTH_FLOAT);
PutChar(tab);
PutReal(lnOccupiedBoxes[sizeIndex], WIDTH_TOTAL, WIDTH_FLOAT);
PutChar(tab);
PutReal(localSlope[sizeIndex], WIDTH_TOTAL, WIDTH_FLOAT);
PutChar(cr);
end;

where.v := 100;
where.h := 100;
SFPutFile(where, 'Save the results as?', concat(title, '.box'),
nil, reply);
if reply.good then
with reply do
SaveAsText(fname, vRefnum);

TextBufSize := 0;
PutString(concat('No. of pts.', tab, '1st box no.', tab,
'Last box no.', tab, '1st box size', tab,
'Last box size', tab, 'Box Dimension', tab,
'Std Error', cr));
smessagel := concat('Pts', tab, 'Dbox');

for j := 7 to NUM_BOX_SIZES - LARGEST_BOX_INDEX + 1 do begin
dbmax := 0.0;
chi2Min := 9999999999.9;
for LAST_BOX_INDEX := NUM_BOX_SIZES downto
LARGEST_BOX_INDEX + j - 1 do begin
FIRST_BOX_INDEX := LAST_BOX_INDEX - j + 1;
sx := 0.0;
sy := 0.0;
st2 := 0.0;
db := 0.0;
for i := FIRST_BOX_INDEX to LAST_BOX_INDEX do begin
sx := sx + lnBoxSizes[i];
sy := sy + lnOccupiedBoxes[i];
end;
ss := LAST_BOX_INDEX - FIRST_BOX_INDEX + 1.0;
sxoss := sx / ss;

for i := FIRST_BOX_INDEX to LAST_BOX_INDEX do begin
t := lnBoxSizes[i] - sxoss;
st2 := st2 + t * t;
db := db + t * lnOccupiedBoxes[i];
end;
db := db / st2;
intcp := (sy - sx * db) / ss;
sintcp := Sqrt((1.0 + sx * sx / (ss * st2)) / ss);
sddb := Sqrt(1.0 / st2);
chi2 := 0.0;

for i := FIRST_BOX_INDEX to LAST_BOX_INDEX do begin
temp1 := lnOccupiedBoxes[i] - intcp - db * lnBoxSizes[i];
chi2 := chi2 + temp1 * temp1;
end;
sigdat := Sqrt(chi2 / (ss - 2.0));
sintcp := sintcp * sigdat;
sddb := sddb * sigdat;
db := 0.0 - db;
if db > dbmax then begin

```

```

    dbmax := db;
    sddbmax := sddb;
    dbmFirst := FIRST_BOX_INDEX;
    dbmLast := LAST_BOX_INDEX;
    end;
    if chi2Min > chi2 then begin
        chi2Min := chi2;
        dbcmn := db;
        sddbcmn := sddb;
        dbcFirst := FIRST_BOX_INDEX;
        dbcLast := LAST_BOX_INDEX;
        end;
    end;
    longtmp1 := j;
    strtemp := concat('MX ', long2str(longtmp1));
    PutString(strtemp);
    PutChar(tab);
    longtmp1 := dbmFirst;
    strtemp := long2str(longtmp1);
    PutString(strtemp);
    PutChar(tab);
    longtmp1 := dbmLast;
    strtemp := long2str(longtmp1);
    PutString(strtemp);
    PutChar(tab);
    longtmp1 := boxSizes[dbmFirst];
    strtemp := long2str(longtmp1);
    PutString(strtemp);
    PutChar(tab);
    longtmp2 := boxSizes[dbmLast];
    strtemp := long2str(longtmp2);
    PutString(strtemp);
    PutChar(tab);
    PutReal(dbmax, WIDTH_TOTAL, WIDTH_FLOAT);
    PutChar(tab);
    PutReal(sddbmax, WIDTH_TOTAL, WIDTH_FLOAT);
    PutChar(cr);

    longtmp1 := j;
    strtemp := concat('BS ', long2str(longtmp1));
    PutString(strtemp);
    PutChar(tab);
    if j < 10 then
        strtemp := concat('0', long2str(longtmp1))
    else
        strtemp := long2str(longtmp1);
    smessage1 := concat(smmessage1, cr, strtemp);
    longtmp1 := dbcFirst;
    strtemp := long2str(longtmp1);
    PutString(strtemp);
    PutChar(tab);
    longtmp1 := dbcLast;
    strtemp := long2str(longtmp1);
    PutString(strtemp);
    PutChar(tab);
    longtmp1 := boxSizes[dbcFirst];
    strtemp := long2str(longtmp1);
    PutString(strtemp);
    PutChar(tab);
    longtmp2 := boxSizes[dbcLast];
    strtemp := long2str(longtmp2);
    PutString(strtemp);
    PutChar(tab);
    PutReal(dbcmn, WIDTH_TOTAL, WIDTH_FLOAT);
    PutChar(tab);
    PutReal(sddbcmn, WIDTH_TOTAL, WIDTH_FLOAT);
    PutChar(cr);

```

```

    dbint := trunc(dbcmn);
    dbdec1 := trunc(dbcmn * 10.0) - dbint * 10;
    dbdec2 := trunc(dbcmn * 100.0) - dbint * 100 - dbdec1 * 10;
    sddbint := trunc(sddbcmn);
    sddbdec1 := trunc(sddbcmn * 10.0) - sddbint * 10;
    sddbdec2 := trunc(sddbcmn * 100.0) - sddbint * 100 -
        sddbdec1 * 10;
    smessage := concat(smmessage1, tab, long2str(dbint), '.',
        long2str(dbdec1), long2str(dbdec2), '±',
        long2str(sddbint), '.', long2str(sddbdec1),
        long2str(sddbdec2));
    ShowMessage(smessage);
    smmessage1 := smmessage;
end;
400

where.v := 100;
where.h := 100;
SFPutFile(where, 'Save the results as?', concat(title, '.slopes'),
    nil, reply);
if reply.good then
    with reply do
        SaveAsText(fname, vRefnum);

    DisposPtr(ptr(imageArray));
end
420
else begin
    PutMessage('This is not a binary image!');
    exit(DoBoxDimension);
end;
end;
end;
end;

```

A.3 Sandbox Algorithm

```

procedure DoSandDimension;
label
    1120;
const
    NUM_BOX_SIZES = 25;
    BOXES_WITH_NO_ITERATIONS = 3;
    INCLUDE_SECONDS = FALSE;
    WIDTH_TOTAL = 10;
    WIDTH_FLOAT = 8;
    MAX_LENGTH = 1024;
type
    ImageType = array[0..MAX_LENGTH, 0..MAX_LENGTH] of Boolean;
    ImageTypePtr = ^ImageType;
var
    imageArray: ImageTypePtr;
    vstart, vend, hstart, hend, width, width1, height, height1, hloc,
        vloc, k, j, i, i9, dbmFirst, dbmLast: integer;
    sizeIndex, e, xs, ys, minLengthY, minLengthX, xr, yr, minLength,
        dbcFirst, dbcLast: integer;
    x0, y0, xStart, yStart, xEnd, yEnd, LARGEST_BOX_INDEX,
        FIRST_BOX_INDEX, LAST_BOX_INDEX: integer;
    longtmp1, longtmp2, mass, configIdx, timeInSeconds, timeZero,
        numParticles, xc, yc, two, numIter: longint;
    dbint, dbdec1, dbdec2, sddbint, sddbdec1, sddbdec2: longint;
    temp1, temp2, dbcmn, sddbcmn: extended;

```

```

sx, sy, st2, db, ss, sxoss, t, intcp, sintcp, sddb, chi2,
    chi2Min, sigdat, dbmax, sddbmax: extended;
theLine: LineType;
boxSizes: array[1..NUM_BOX_SIZES] of integer;
totalMass: array[1..NUM_BOX_SIZES] of longint;
lnBoxSizes, lnTotalMass, localSlope:
    array[1..NUM_BOX_SIZES] of extended;
smessage, smessage1, timeString, strtemp: Str255;
where: point;
reply: SFReply;
AutoSelectAll: Boolean;
begin
with info^ do begin
if BinaryPic then begin
TextBufSize := 0;
boxSizes[1] := 512;
temp1 := 512.0;
for k := 2 to NUM_BOX_SIZES do begin
repeat
temp2 := 0.793700526 * temp1;
j := round(temp2);
temp1 := temp2
until j <> boxSizes[k - 1];
boxSizes[k] := j;
end;

AutoSelectAll := not RoiShowing;
if AutoSelectAll then
SelectAll(false);

if roiType <> RectRoi then begin
PutMessage('I can only deal with a rectangular ROI!');
exit(DoSandDimension);
end;

with RoiRect do begin
hend := right;
vend := bottom;
vstart := top;
hstart := left;
width := right - left;
height := bottom - top;
end;
width1 := width - 1;
height1 := height - 1;

numParticles := 0;
smessage := concat('Idx', tab, 'Size');

imageArray := ImageTypePtr(NewPtr(SizeOf(ImageType)));
if imageArray = nil then begin
DisposPtr(ptr(imageArray));
PutMessage('Insufficient memory');
exit(DoSandDimension);
end;
if (height > MAX_LENGTH) or (width > MAX_LENGTH) then begin
longtmp1 := MAX_LENGTH;
DisposPtr(ptr(imageArray));
PutMessage(concat('Image width/length must be less than ',
long2str(longtmp1), ' for dimension calculation!',
cr, 'Change MAX_LENGTH constant in source code for
larger image.'));
exit(DoSandDimension);
end;
for vloc := 0 to height1 do begin
GetLine(hStart, vloc + vstart, width, theLine);
for hloc := 0 to width1 do begin
if theLine[hloc] = 0 then

```

```

    imageArray^[hloc, vloc] := FALSE
  else begin
    numParticles := numParticles + 1;
    imageArray^[hloc, vloc] := TRUE;
  end;
end;
end;
100

GetDateTime(timeZero);

{  Find center of mass  }
xc := 0;
yc := 0;
for vloc := 0 to height1 do begin
  for hloc := 0 to width1 do begin
    if imageArray^[hloc, vloc] then begin
      xc := xc + hloc;
      yc := yc + vloc;
    end;
  end;
end;
xc := round(xc / numParticles);
yc := round(yc / numParticles);

if xc < yc then begin
  if xc < width - xc - 1 then begin
    if xc < height - yc - 1 then begin
      minLength := xc;
    end
  else begin
    minLength := height - yc - 1;
  end;
end
else begin
  if width - xc - 1 < height - yc - 1 then begin
    minLength := width - xc - 1;
  end
  else begin
    minLength := height - yc - 1;
  end;
end;
end
else begin
  if yc < width - xc - 1 then begin
    if yc < height - yc - 1 then begin
      minLength := yc;
    end
  else begin
    minLength := height - yc - 1;
  end;
end
else begin
  if width - xc - 1 < height - yc - 1 then begin
    minLength := width - xc - 1;
  end
  else begin
    minLength := height - yc - 1;
  end;
end;
end;

minLength := minLength div 2;

for i := 0 to minLength do begin
  for vloc := -i to i do begin
    for hloc := -i to i do begin
      if imageArray^[(xc + hloc), (yc + vloc)] then begin
        xc := xc + hloc;

```

```

        yc := yc + vloc;
        goto 1120;
    end;
end;
end;
end;
PutMessage('Could not find occupied pixel around center of mass');
exit(DoSandDimension);
170
1120:
if xc < width - xc - 1 then
    minLengthX := xc
else
    minLengthX := width - xc - 1;

if yc < height - yc - 1 then
    minLengthY := yc
else
    minLengthY := height - yc - 1;
180

if minLengthY < minLengthX then
    minLength := minLengthY
else
    minLength := minLengthX;

minLength := minLength div 2;
minLengthX := minLengthX div 2;
minLengthY := minLengthY div 2;
190

LARGEST_BOX_INDEX := 1;
while (boxSizes[LARGEST_BOX_INDEX] >= minLength) do begin
    LARGEST_BOX_INDEX := LARGEST_BOX_INDEX + 1;
end;

ShowMessage(concat(long2str(minLength), cr, 'CM: ', long2str(xc),
    ', ', long2str(yc)));

for k := LARGEST_BOX_INDEX to NUM_BOX_SIZES do begin
    longtmp1 := k;
    longtmp2 := boxSizes[k];
    if k < 10 then
        smessage := concat(smessage, cr, '0', long2str(longtmp1),
            tab, long2str(longtmp2))
    else
        smessage := concat(smessage, cr, long2str(longtmp1), tab,
            long2str(longtmp2));
end;
200

smessage := '';
smessage1 := '';

PutString(concat('Number', tab, 'Box Size', tab, 'Total Mass',
    tab, 'ln [Box Size]', tab, 'ln [Total Mass]',
    tab, 'Local Slope', cr));

{ Find mass per radius }

for sizeIndex := LARGEST_BOX_INDEX to NUM_BOX_SIZES do begin
    totalMass[sizeIndex] := 0;
    lnBoxSizes[sizeIndex] := Ln(2 * boxSizes[sizeIndex] + 1);
end;
220

two := 2;
numIter := (two * minLengthX + 1) * (two * minLengthY + 1);
configIdx := 0;
for yr := (yc - minLengthY) to (yc + minLengthY) do begin
    for xr := (xc - minLengthX) to (xc + minLengthX) do begin
        if imageArray[xr, yr] then begin

```

```

configIdx := configIdx + 1;
for sizeIdx := LARGEST_BOX_INDEX to NUM_BOX_SIZES do begin
    mass := 0;
    yStart := yr - boxSizes[sizeIdx];
    yEnd := yr + boxSizes[sizeIdx];
    xStart := xr - boxSizes[sizeIdx];
    xEnd := xr + boxSizes[sizeIdx];
    for vloc := yStart to yEnd do begin
        for hloc := xStart to xEnd do begin
            if imageArray[hloc, vloc] then
                mass := mass + 1;
            end;
        end;
        totalMass[sizeIdx] := totalMass[sizeIdx] + mass;
    end;
end;
end;

GetDateTime(timeInSeconds);
timeInSeconds := timeInSeconds - timeZero;
IUTimeString(timeInSeconds, INCLUDE_SECONDS, timeString);
ShowMessage(concat('Time: ', timeString, cr, 'Iteration: ',
    long2str(configIdx), cr, 'Area: ', long2str(numIter)));

end;

for sizeIdx := LARGEST_BOX_INDEX to NUM_BOX_SIZES do begin
    lnTotalMass[sizeIdx] := Ln(totalMass[sizeIdx] / configIdx);
end;

for sizeIdx := LARGEST_BOX_INDEX to NUM_BOX_SIZES do begin
    if (sizeIdx > LARGEST_BOX_INDEX + 1) and
        (sizeIdx < NUM_BOX_SIZES - 1) then begin
        sx := 0.0;
        sy := 0.0;
        st2 := 0.0;
        db := 0.0;
        for i9 := sizeIdx - 2 to sizeIdx + 2 do begin
            sx := sx + lnBoxSizes[i9];
            sy := sy + lnTotalMass[i9];
        end;
        ss := 5.0; {number of points to calculate local slope}
        sxoss := sx / ss;
        for i9 := sizeIdx - 2 to sizeIdx + 2 do begin
            t := lnBoxSizes[i9] - sxoss;
            st2 := st2 + t * t;
            db := db + t * lnTotalMass[i9];
        end;
        db := db / st2;
        localSlope[sizeIdx] := db;
    end
    else
        localSlope[sizeIdx] := 0.0;

    longtmp1 := sizeIdx;
    strtemp := long2str(longtmp1);
    PutString(strtemp);
    PutChar(tab);
    longtmp1 := 2 * boxSizes[sizeIdx] + 1;
    strtemp := long2str(longtmp1);
    PutString(strtemp);
    PutChar(tab);
    longtmp2 := totalMass[sizeIdx];
    strtemp := long2str(longtmp2);
    PutString(strtemp);
    PutChar(tab);
    PutReal(lnBoxSizes[sizeIdx], WIDTH_TOTAL, WIDTH_FLOAT);

```



```

PutChar(tab);
PutReal(lnTotalMass[sizeIndex], WIDTH_TOTAL, WIDTH_FLOAT);
PutChar(tab);
PutReal(localSlope[sizeIndex], WIDTH_TOTAL, WIDTH_FLOAT);
PutChar(cr);
end;

where.v := 100;
where.h := 100;
SFPutFile(where, 'Save the results as?', concat(title, '.sand'),
nil, reply);
if reply.good then
with reply do
SaveAsText(fname, vRefnum);

TextBufSize := 0;
PutString(concat('No. of pts.', tab, '1st box no.', tab,
'Last box no.', tab, '1st box size', tab,
'Last box size', tab, 'Sandbox Dimension',
tab, 'Std Error', cr));
smessage1 := concat('Pts', tab, 'Dbox');

for j := 7 to NUM_BOX_SIZES - LARGEST_BOX_INDEX + 1 do begin
dbmax := 0.0;
chi2Min := 999999999.9;
for LAST_BOX_INDEX := NUM_BOX_SIZES downto
LARGEST_BOX_INDEX + j - 1 do begin
FIRST_BOX_INDEX := LAST_BOX_INDEX - j + 1;
sx := 0.0;
sy := 0.0;
st2 := 0.0;
db := 0.0;
for i := FIRST_BOX_INDEX to LAST_BOX_INDEX do begin
sx := sx + lnBoxSizes[i];
sy := sy + lnTotalMass[i];
end;
ss := LAST_BOX_INDEX - FIRST_BOX_INDEX + 1.0;
sxoss := sx / ss;

for i := FIRST_BOX_INDEX to LAST_BOX_INDEX do begin
t := lnBoxSizes[i] - sxoss;
st2 := st2 + t * t;
db := db + t * lnTotalMass[i];
end;
db := db / st2;
intcp := (sy - sx * db) / ss;
sintcp := Sqrt((1.0 + sx * sx / (ss * st2)) / ss);
sddb := Sqrt(1.0 / st2);
chi2 := 0.0;

for i := FIRST_BOX_INDEX to LAST_BOX_INDEX do begin
temp1 := lnTotalMass[i] - intcp - db * lnBoxSizes[i];
chi2 := chi2 + temp1 * temp1;
end;
sigdat := Sqrt(chi2 / (ss - 2.0));
sintcp := sintcp * sigdat;
sddb := sddb * sigdat;
if db > dbmax then begin
dbmax := db;
sddbmax := sddb;
dbmFirst := FIRST_BOX_INDEX;
dbmLast := LAST_BOX_INDEX;
end;
if chi2Min > chi2 then begin
chi2Min := chi2;
dbcmin := db;
sddbmin := sddb;
dbcFirst := FIRST_BOX_INDEX;

```

```

    dbcLast := LAST_BOX_INDEX;
    end;
end;

longtmp1 := j;
strtemp := concat('MX ', long2str(longtmp1));
PutString(strtemp);
PutChar(tab);
longtmp1 := dbmFirst;
strtemp := long2str(longtmp1);
PutString(strtemp);
PutChar(tab);
longtmp1 := dbmLast;
strtemp := long2str(longtmp1);
PutString(strtemp);
PutChar(tab);
longtmp1 := 2 * boxSizes[dbmFirst] + 1;
strtemp := long2str(longtmp1);
PutString(strtemp);
PutChar(tab);
longtmp2 := 2 * boxSizes[dbmLast] + 1;
strtemp := long2str(longtmp2);
PutString(strtemp);
PutChar(tab);
PutReal(dbmax, WIDTH_TOTAL, WIDTH_FLOAT);
PutChar(tab);
PutReal(sddbmax, WIDTH_TOTAL, WIDTH_FLOAT);
PutChar(cr);

longtmp1 := j;
strtemp := concat('BS ', long2str(longtmp1));
PutString(strtemp);
PutChar(tab);
if j < 10 then
    strtemp := concat('0', long2str(longtmp1))
else
    strtemp := long2str(longtmp1);
smessage1 := concat(smmessage1, cr, strtemp);
longtmp1 := dbcFirst;
strtemp := long2str(longtmp1);
PutString(strtemp);
PutChar(tab);
longtmp1 := dbcLast;
strtemp := long2str(longtmp1);
PutString(strtemp);
PutChar(tab);
longtmp1 := 2 * boxSizes[dbcFirst] + 1;
strtemp := long2str(longtmp1);
PutString(strtemp);
PutChar(tab);
longtmp2 := 2 * boxSizes[dbcLast] + 1;
strtemp := long2str(longtmp2);
PutString(strtemp);
PutChar(tab);
PutReal(dbcmin, WIDTH_TOTAL, WIDTH_FLOAT);
PutChar(tab);
PutReal(sddbmin, WIDTH_TOTAL, WIDTH_FLOAT);
PutChar(cr);

dbint := trunc(dbcmin);
dbdec1 := trunc(dbcmin * 10.0) - dbint * 10;
dbdec2 := trunc(dbcmin * 100.0) - dbint * 100 - dbdec1 * 10;
sddbint := trunc(sddbmin);
sddbdec1 := trunc(sddbmin * 10.0) - sddbint * 10;
sddbdec2 := trunc(sddbmin * 100.0) - sddbint * 100 -
    sddbdec1 * 10;
smmessage := concat(smmessage1, tab, long2str(dbint), '.',

```

```

                long2str(dbdec1), long2str(dbdec2), '±',
                long2str(sddbint), '.', long2str(sddbdec1),
                long2str(sddbdec2));
    ShowMessage(smmessage);
    smmessage1 := smmessage;
end;
440

where.v := 100;
where.h := 100;
SFPutFile(where, 'Save the results as?', concat(title, '.slopes'),
    nil, reply);
if reply.good then
    with reply do
        SaveAsText(fname, vRefnum);

        DisposPtr(ptr(imageArray));
450

    end
else begin
    PutMessage('This is not a binary image!');
    exit(DoSandDimension);
end;
end;
end;
end;

```

A.4 Correlation Algorithm

```

procedure DoCorrDimension;
label
    1120;
const
    NUM_BOX_SIZES = 25;
    EMBEDDING_DIM = 2;
    INCLUDE_SECONDS = FALSE;
    WIDTH_TOTAL = 10;
    WIDTH_FLOAT = 8;
    MAX_LENGTH = 1024;
10
type
    ImageType = array[0..MAX_LENGTH, 0..MAX_LENGTH] of Boolean;
    ImageTypePtr = ^ImageType;
var
    imageArray: ImageTypePtr;
    vstart, vend, hstart, hend, width, width1, height, height1, hloc,
        vloc, k, j, i, i9, dbmFirst, dbmLast: integer;
    sizeIndex, e, xs, ys, minLengthY, minLengthX, xr, yr, minLength,
        dbcFirst, dbcLast: integer;
20
    x0, y0, xStart, yStart, xEnd, yEnd, LARGEST_BOX_INDEX,
        FIRST_BOX_INDEX, LAST_BOX_INDEX: integer;
    longtmp1, longtmp2, mass, configIdx, timeInSeconds, timeZero,
        numParticles, xc, yc, two, numIter: longint;
    dbint, dbdec1, dbdec2, sddbint, sddbdec1, sddbdec2: longint;
    temp1, temp2, dbcmin, sddbcmin, distance: extended;
    sx, sy, st2, db, ss, sxoss, t, intcp, sintcp, sddb, chi2, chi2Min,
        sigdat, dbmax, sddbmax: extended;

    theLine: LineType;
    boxSizes: array[1..NUM_BOX_SIZES] of integer;
    totalMass: array[1..NUM_BOX_SIZES] of longint;
30
    lnBoxSizes, lnTotalMass, localSlope, normalizationFactor:
        array[1..NUM_BOX_SIZES] of extended;
    smmessage, smmessage1, timeString, strtemp: Str255;

```

```

where: point;
reply: SFReply;
AutoSelectAll: Boolean;
begin
with info^ do begin
if BinaryPic then begin
    TextBufSize := 0;
    boxSizes[1] := 512;
    temp1 := 512.0;
    for k := 2 to NUM_BOX_SIZES do begin
        repeat
            temp2 := 0.793700526 * temp1;
            j := round(temp2);
            temp1 := temp2
        until j <> boxSizes[k - 1];
        boxSizes[k] := j;
    end;

    AutoSelectAll := not RoiShowing;
    if AutoSelectAll then
        SelectAll(false);

    if roiType <> RectRoi then begin
        PutMessage('I can only deal with a rectangular ROI!');
        exit(DoCorrDimension);
    end;

    with RoiRect do begin
        hend := right;
        vend := bottom;
        vstart := top;
        hstart := left;
        width := right - left;
        height := bottom - top;
    end;
    width1 := width - 1;
    height1 := height - 1;

    numParticles := 0;
    smessage := concat('Idx', tab, 'Size');

    imageArray := ImageTypePtr(NewPtr(SizeOf(ImageType)));
    if imageArray = nil then begin
        DisposPtr(ptr(imageArray));
        PutMessage('Insufficient memory');
        exit(DoCorrDimension);
    end;
    if (height > MAX_LENGTH) or (width > MAX_LENGTH) then begin
        longtmp1 := MAX_LENGTH;
        DisposPtr(ptr(imageArray));
        PutMessage(concat('Image width/length must be less than ',
            long2str(longtmp1), ' for dimension calculation!',
            cr, 'Change MAX_LENGTH constant in source code for
            larger image.'));
        exit(DoCorrDimension);
    end;
    for vloc := 0 to height1 do begin
        GetLine(hStart, vloc + vstart, width, theLine);
        for hloc := 0 to width1 do begin
            if theLine[hloc] = 0 then
                imageArray^[hloc, vloc] := FALSE
            else begin
                numParticles := numParticles + 1;
                imageArray^[hloc, vloc] := TRUE;
            end;
        end;
    end;
end;
end;

```

```

GetDateTime(timeZero);

{ Find center of mass }
xc := 0;
yc := 0;
for vloc := 0 to height1 do begin
  for hloc := 0 to width1 do begin
    if imageArray^[hloc, vloc] then begin
      xc := xc + hloc;
      yc := yc + vloc;
    end;
  end;
end;
xc := round(xc / numParticles);
yc := round(yc / numParticles);

if xc < yc then begin
  if xc < width - xc - 1 then begin
    if xc < height - yc - 1 then begin
      minLength := xc;
    end
  else begin
    minLength := height - yc - 1;
  end;
end
else begin
  if width - xc - 1 < height - yc - 1 then begin
    minLength := width - xc - 1;
  end
else begin
    minLength := height - yc - 1;
  end;
end;
end
else begin
  if yc < width - xc - 1 then begin
    if yc < height - yc - 1 then begin
      minLength := yc;
    end
  else begin
    minLength := height - yc - 1;
  end;
end
else begin
  if width - xc - 1 < height - yc - 1 then begin
    minLength := width - xc - 1;
  end
else begin
    minLength := height - yc - 1;
  end;
end;
end;

minLength := minLength div 2;

for i := 0 to minLength do begin
  for vloc := -i to i do begin
    for hloc := -i to i do begin
      if imageArray^[xc + hloc, yc + vloc] then begin
        xc := xc + hloc;
        yc := yc + vloc;
        goto 1120;
      end;
    end;
  end;
end;
PutMessage('Could not find occupied pixel around center of mass');
exit(DoCorrDimension);

```

```

1120:
    if xc < width - xc - 1 then
        minLengthX := xc
    else
        minLengthX := width - xc - 1;

    if yc < height - yc - 1 then
        minLengthY := yc
    else
        minLengthY := height - yc - 1;

    if minLengthY < minLengthX then
        minLength := minLengthY
    else
        minLength := minLengthX;

    minLength := minLength div 2;
    minLengthX := minLengthX div 2;
    minLengthY := minLengthY div 2;

    LARGEST_BOX_INDEX := 1;
    while (boxSizes[LARGEST_BOX_INDEX] >= trunc(minLength / 1.1))
    do begin
        LARGEST_BOX_INDEX := LARGEST_BOX_INDEX + 1;
    end;

    ShowMessage(concat(long2str(minLength), cr, 'CM: ',
        long2str(xc), ', ', long2str(yc)));

    for k := LARGEST_BOX_INDEX to NUM_BOX_SIZES do begin
        longtmp1 := k;
        longtmp2 := boxSizes[k];
        if k < 10 then
            smessage := concat(smessage, cr, '0', long2str(longtmp1),
                tab, long2str(longtmp2))
        else
            smessage := concat(smessage, cr, long2str(longtmp1), tab,
                long2str(longtmp2));
        end;

    smessage := '';
    smessage1 := '';

    PutString(concat('Number', tab, 'Radius', tab, 'Total Mass',
        tab, 'ln [Radius]', tab, 'ln [Norm Mass]', tab,
        'Local Slope', cr));

    { Find mass per ring }

    for sizeIndex := LARGEST_BOX_INDEX to NUM_BOX_SIZES do begin
        totalMass[sizeIndex] := 0;
        lnBoxSizes[sizeIndex] := Ln(2 * boxSizes[sizeIndex] + 1);
    end;

    two := 2;
    numlter := (two * minLengthX + 1) * (two * minLengthY + 1);
    configIdx := 0;
    for yr := (yc - minLengthY) to (yc + minLengthY) do begin
        for xr := (xc - minLengthX) to (xc + minLengthX) do begin
            if imageArray^ [xr, yr] then begin
                configIdx := configIdx + 1;
                for sizeIndex := LARGEST_BOX_INDEX to NUM_BOX_SIZES do begin
                    mass := 0;
                    yStart := yr - round(1.1 * boxSizes[sizeIndex]);
                    yEnd := yr + round(1.1 * boxSizes[sizeIndex]);
                    xStart := xr - round(1.1 * boxSizes[sizeIndex]);
                    xEnd := xr + round(1.1 * boxSizes[sizeIndex]);

```

```

    for vloc := yStart to yEnd do begin
      for hloc := xStart to xEnd do begin
        if imageArray^[hloc, vloc] then begin
          distance := sqrt(1.0 * (hloc - xr) * (hloc - xr) +
            1.0 * (vloc - yr) * (vloc - yr));
          if ((distance <= 1.1 * boxSizes[sizeIndex]) and
            (distance >= 1.0 * boxSizes[sizeIndex])) then
            mass := mass + 1;
          end;
        end;
      end;
      totalMass[sizeIndex] := totalMass[sizeIndex] + mass;
    end;
  end;
end;

GetDateTime(timeInSeconds);
timeInSeconds := timeInSeconds - timeZero;
IUTimeString(timeInSeconds, INCLUDE_SECONDS, timeString);
ShowMessage(concat('Time: ', timeString, cr, 'Iteration: ',
  long2str(configIdx), cr, 'Area: ', long2str(numIter)));

end;

for sizeIndex := LARGEST_BOX_INDEX to NUM_BOX_SIZES do begin
  mass := 0;
  yStart := -round(1.1 * boxSizes[sizeIndex]);
  yEnd := round(1.1 * boxSizes[sizeIndex]);
  xStart := -round(1.1 * boxSizes[sizeIndex]);
  xEnd := round(1.1 * boxSizes[sizeIndex]);
  for vloc := yStart to yEnd do begin
    for hloc := xStart to xEnd do begin
      distance := sqrt(1.0 * hloc * hloc + 1.0 * vloc * vloc);
      if ((distance <= 1.1 * boxSizes[sizeIndex]) and (distance >= 1.0 * boxSizes[sizeIndex])) then
        mass := mass + 1;
      end;
    end;
  end;
  normalizationFactor[sizeIndex] := 1.0 * mass;
end;

for sizeIndex := LARGEST_BOX_INDEX to NUM_BOX_SIZES do begin
  lnTotalMass[sizeIndex] := Ln(totalMass[sizeIndex] /
    (configIdx * normalizationFactor[sizeIndex]));
end;

for sizeIndex := LARGEST_BOX_INDEX to NUM_BOX_SIZES do begin
  if (sizeIndex > LARGEST_BOX_INDEX + 1) and
    (sizeIndex < NUM_BOX_SIZES - 1) then begin
    sx := 0.0;
    sy := 0.0;
    st2 := 0.0;
    db := 0.0;
    for i9 := sizeIndex - 2 to sizeIndex + 2 do begin
      sx := sx + lnBoxSizes[i9];
      sy := sy + lnTotalMass[i9];
    end;
    ss := 5.0; {number of points to calculate local slope}
    sxoss := sx / ss;
    for i9 := sizeIndex - 2 to sizeIndex + 2 do begin
      t := lnBoxSizes[i9] - sxoss;
      st2 := st2 + t * t;
      db := db + t * lnTotalMass[i9];
    end;
    db := db / st2;
    localSlope[sizeIndex] := db + EMBEDDING_DIM;
  end
else

```

```

localSlope[sizeIndex] := 0.0;

longtmp1 := sizeIndex;
strtemp := long2str(longtmp1);
PutString(strtemp);
PutChar(tab);
longtmp1 := boxSizes[sizeIndex];
strtemp := long2str(longtmp1);
PutString(strtemp);
PutChar(tab);
longtmp2 := totalMass[sizeIndex];
strtemp := long2str(longtmp2);
PutString(strtemp);
PutChar(tab);
PutReal(lnBoxSizes[sizeIndex], WIDTH_TOTAL, WIDTH_FLOAT);
PutChar(tab);
PutReal(lnTotalMass[sizeIndex], WIDTH_TOTAL, WIDTH_FLOAT);
PutChar(tab);
PutReal(localSlope[sizeIndex], WIDTH_TOTAL, WIDTH_FLOAT);
PutChar(cr);
end;

where.v := 100;
where.h := 100;
SFPutFile(where, 'Save the results as?', concat(title, '.corr'),
nil, reply);
if reply.good then
with reply do
SaveAsText(fname, vRefnum);

TextBufSize := 0;
PutString(concat('No. of pts.', tab, '1st rad no.', tab,
'Last rad no.', tab, '1st rad size', tab,
'Last rad size', tab, 'Corr Dimension', tab,
'Std Error', cr));
smessage1 := concat('Pts', tab, 'Dbox');

for j := 7 to NUM_BOX_SIZES - LARGEST_BOX_INDEX + 1 do begin
dbmax := 0.0;
chi2Min := 999999999.9;
for LAST_BOX_INDEX := NUM_BOX_SIZES downto
LARGEST_BOX_INDEX + j - 1 do begin
FIRST_BOX_INDEX := LAST_BOX_INDEX - j + 1;
sx := 0.0;
sy := 0.0;
st2 := 0.0;
db := 0.0;
for i := FIRST_BOX_INDEX to LAST_BOX_INDEX do begin
sx := sx + lnBoxSizes[i];
sy := sy + lnTotalMass[i];
end;
ss := LAST_BOX_INDEX - FIRST_BOX_INDEX + 1.0;
sxoss := sx / ss;

for i := FIRST_BOX_INDEX to LAST_BOX_INDEX do begin
t := lnBoxSizes[i] - sxoss;
st2 := st2 + t * t;
db := db + t * lnTotalMass[i];
end;
db := db / st2;
intcp := (sy - sx * db) / ss;
sintcp := Sqrt((1.0 + sx * sx / (ss * st2)) / ss);
sddb := Sqrt(1.0 / st2);
chi2 := 0.0;

for i := FIRST_BOX_INDEX to LAST_BOX_INDEX do begin
temp1 := lnTotalMass[i] - intcp - db * lnBoxSizes[i];
chi2 := chi2 + temp1 * temp1;

```



```

    end;
    sigdat := Sqrt(chi2 / (ss - 2.0));
    sintcp := sintcp * sigdat;
    sddb := sddb * sigdat;

    db := db + EMBEDDING_DIM;
    if db > dbmax then begin
        dbmax := db;
        sddbmax := sddb;
        dbmFirst := FIRST_BOX_INDEX;
        dbmLast := LAST_BOX_INDEX;
        end;
    if chi2Min > chi2 then begin
        chi2Min := chi2;
        dbcmn := db;
        sddbcmn := sddb;
        dbcFirst := FIRST_BOX_INDEX;
        dbcLast := LAST_BOX_INDEX;
        end;
    end;

    longtmp1 := j;
    strtemp := concat('MX ', long2str(longtmp1));
    PutString(strtemp);
    PutChar(tab);
    longtmp1 := dbmFirst;
    strtemp := long2str(longtmp1);
    PutString(strtemp);
    PutChar(tab);
    longtmp1 := dbmLast;
    strtemp := long2str(longtmp1);
    PutString(strtemp);
    PutChar(tab);
    longtmp1 := boxSizes[dbmFirst];
    strtemp := long2str(longtmp1);
    PutString(strtemp);
    PutChar(tab);
    longtmp2 := boxSizes[dbmLast];
    strtemp := long2str(longtmp2);
    PutString(strtemp);
    PutChar(tab);
    PutReal(dbmax, WIDTH_TOTAL, WIDTH_FLOAT);
    PutChar(tab);
    PutReal(sddbmax, WIDTH_TOTAL, WIDTH_FLOAT);
    PutChar(cr);

    longtmp1 := j;
    strtemp := concat('BS ', long2str(longtmp1));
    PutString(strtemp);
    PutChar(tab);
    if j < 10 then
        strtemp := concat('0', long2str(longtmp1))
    else
        strtemp := long2str(longtmp1);
    smessage1 := concat(smessage1, cr, strtemp);
    longtmp1 := dbcFirst;
    strtemp := long2str(longtmp1);
    PutString(strtemp);
    PutChar(tab);
    longtmp1 := dbcLast;
    strtemp := long2str(longtmp1);
    PutString(strtemp);
    PutChar(tab);
    longtmp1 := boxSizes[dbcFirst];
    strtemp := long2str(longtmp1);
    PutString(strtemp);
    PutChar(tab);
    longtmp2 := boxSizes[dbcLast];

```

```

strtemp := long2str(longtmp2);
PutString(strtemp);
PutChar(tab);
PutReal(dbcmn, WIDTH_TOTAL, WIDTH_FLOAT);
PutChar(tab);
PutReal(sddbcmn, WIDTH_TOTAL, WIDTH_FLOAT);
PutChar(cr);

dbint := trunc(dbcmn);
dbdec1 := trunc(dbcmn * 10.0) - dbint * 10;
dbdec2 := trunc(dbcmn * 100.0) - dbint * 100 - dbdec1 * 10;
sddbint := trunc(sddbcmn);
sddbdec1 := trunc(sddbcmn * 10.0) - sddbint * 10;
sddbdec2 := trunc(sddbcmn * 100.0) - sddbint * 100 -
sddbdec1 * 10;
smessage := concat(smmessage1, tab, long2str(dbint), '.',
long2str(dbdec1), long2str(dbdec2), '±',
long2str(sddbint), '.', long2str(sddbdec1),
long2str(sddbdec2));
ShowMessage(smmessage);
smmessage1 := smmessage;
end;

where.v := 100;
where.h := 100;
SFPutFile(where, 'Save the results as?', concat(title, '.slopes'),
nil, reply);
if reply.good then
with reply do
SaveAsText(fname, vRefnum);

DisposPtr(ptr(imageArray));

end
else begin
PutMessage('This is not a binary image!');
exit(DoCorrDimension);
end;
end;
end;

```

A.5 Minimum-Path Algorithms

A.5.1 Minimum-Path Identification

```

procedure DoFindMinPath;
const
  MAX_LENGTH = 640;
type
  ImageType = array[0..MAX_LENGTH, 0..MAX_LENGTH] of integer;
  ImageTypePtr = ^ImageType;
var
  vstart, vend, hstart, hend, width, width1, width2, height, height1,
  height2, hloc, vloc: integer;
  stepIndex, breakPoint, x, y, xe, ye, xs, ys: integer;
  longtmp1: longint;
  imageArray: ImageTypePtr;
  theLine: LineType;
  AutoSelectAll, BreakThrough, noProgress: Boolean;
begin

```

```

with info^ do begin
  if BinaryPic then begin

    AutoSelectAll := not RoiShowing;
    if AutoSelectAll then
      SelectAll(false);

    if roiType <> RectRoi then begin
      PutMessage('I can only deal with a rectangular ROI!');
      exit(DoFindMinPath);
    end;

    with RoiRect do begin
      hend := right;
      vend := bottom;
      vstart := top;
      hstart := left;
      width := right - left;
      width1 := width - 1;
      width2 := width - 2;
      height := bottom - top;
      height1 := height - 1;
      height2 := height - 2;
    end;

    imageArray := ImageTypePtr(NewPtr(SizeOf(ImageType)));
    if imageArray = nil then begin
      DisposPtr(ptr(imageArray));
      PutMessage('Insufficient memory');
      exit(DoFindMinPath);
    end;

    for vloc := 0 to height1 do begin
      for hloc := 0 to width1 do begin
        imageArray^[hloc, vloc] := 0;
      end;
    end;

    noProgress := TRUE;
    BreakThrough := FALSE;
    stepIndex := 1;
    GetLine(hstart, vstart, width, theLine);
    for hloc := 0 to width1 do begin
      if theLine[hloc] = 255 then begin
        imageArray^[hloc, 0] := stepIndex;
      end;
    end;

    repeat
      vloc := 0;
      hloc := 0;
      if imageArray^[hloc, vloc] = stepIndex then begin
        GetLine(hstart, vloc + vstart, width, theLine);
        if (theLine[hloc + 1] = 255) and
          (imageArray^[hloc + 1, vloc] = 0) then
          imageArray^[hloc + 1, vloc] := stepIndex + 1;
        GetLine(hstart, vloc + vstart + 1, width, theLine);
        if (theLine[hloc] = 255) and (imageArray^[hloc, vloc + 1] = 0) then
          imageArray^[hloc, vloc + 1] := stepIndex + 1;
        if (theLine[hloc + 1] = 255) and
          (imageArray^[hloc + 1, vloc + 1] = 0) then
          imageArray^[hloc + 1, vloc + 1] := stepIndex + 1;
        noProgress := FALSE;
      end;

    for hloc := 1 to width2 do begin
      if imageArray^[hloc, vloc] = stepIndex then begin
        GetLine(hstart, vloc + vstart, width, theLine);

```

```

if (theLine[hloc - 1] = 255) and
  (imageArray^[hloc - 1, vloc] = 0) then
  imageArray^[hloc - 1, vloc] := stepIndex + 1;
if (theLine[hloc + 1] = 255) and
  (imageArray^[hloc + 1, vloc] = 0) then
  imageArray^[hloc + 1, vloc] := stepIndex + 1;
                                                                 90

GetLine(hstart, vloc + vstart + 1, width, theLine);
if (theLine[hloc - 1] = 255) and
  (imageArray^[hloc - 1, vloc + 1] = 0) then
  imageArray^[hloc - 1, vloc + 1] := stepIndex + 1;
if (theLine[hloc] = 255) and (imageArray^[hloc, vloc + 1] = 0) then
  imageArray^[hloc, vloc + 1] := stepIndex + 1;
if (theLine[hloc + 1] = 255) and
  (imageArray^[hloc + 1, vloc + 1] = 0) then
  imageArray^[hloc + 1, vloc + 1] := stepIndex + 1;
noProgress := FALSE;
end;
                                                                 100
end;

hloc := width1;
if imageArray^[hloc, vloc] = stepIndex then begin
  GetLine(hstart, vloc + vstart, width, theLine);
  if (theLine[hloc - 1] = 255) and
    (imageArray^[hloc - 1, vloc] = 0) then
    imageArray^[hloc - 1, vloc] := stepIndex + 1;
  GetLine(hstart, vloc + vstart + 1, width, theLine);
  if (theLine[hloc - 1] = 255) and
    (imageArray^[hloc - 1, vloc + 1] = 0) then
    imageArray^[hloc - 1, vloc + 1] := stepIndex + 1;
  if (theLine[hloc] = 255) and (imageArray^[hloc, vloc + 1] = 0) then
    imageArray^[hloc, vloc + 1] := stepIndex + 1;
  noProgress := FALSE;
end;
                                                                 110

for vloc := 1 to height2 do begin
  hloc := 0;
                                                                 120
  if imageArray^[hloc, vloc] = stepIndex then begin
    GetLine(hstart, vloc + vstart, width, theLine);
    if (theLine[hloc + 1] = 255) and
      (imageArray^[hloc + 1, vloc] = 0) then
      imageArray^[hloc + 1, vloc] := stepIndex + 1;
    GetLine(hstart, vloc + vstart - 1, width, theLine);
    if (theLine[hloc] = 255) and (imageArray^[hloc, vloc - 1] = 0) then
      imageArray^[hloc, vloc - 1] := stepIndex + 1;
    if (theLine[hloc + 1] = 255) and
      (imageArray^[hloc + 1, vloc - 1] = 0) then
      imageArray^[hloc + 1, vloc - 1] := stepIndex + 1;
    GetLine(hstart, vloc + vstart + 1, width, theLine);
    if (theLine[hloc] = 255) and (imageArray^[hloc, vloc + 1] = 0) then
      imageArray^[hloc, vloc + 1] := stepIndex + 1;
    if (theLine[hloc + 1] = 255) and
      (imageArray^[hloc + 1, vloc + 1] = 0) then
      imageArray^[hloc + 1, vloc + 1] := stepIndex + 1;
    noProgress := FALSE;
    end;
                                                                 130
  for hloc := 1 to width2 do begin
                                                                 140
    if imageArray^[hloc, vloc] = stepIndex then begin
      GetLine(hstart, vloc + vstart, width, theLine);
      if (theLine[hloc - 1] = 255) and
        (imageArray^[hloc - 1, vloc] = 0) then
        imageArray^[hloc - 1, vloc] := stepIndex + 1;
      if (theLine[hloc + 1] = 255) and
        (imageArray^[hloc + 1, vloc] = 0) then
        imageArray^[hloc + 1, vloc] := stepIndex + 1;

      GetLine(hstart, vloc + vstart - 1, width, theLine);
      if (theLine[hloc - 1] = 255) and

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    (imageArray^[hloc - 1, vloc - 1] = 0) then
    imageArray^[hloc - 1, vloc - 1] := stepIndex + 1;
if (theLine[hloc] = 255) and
    (imageArray^[hloc, vloc - 1] = 0) then
    imageArray^[hloc, vloc - 1] := stepIndex + 1;
if (theLine[hloc + 1] = 255) and
    (imageArray^[hloc + 1, vloc - 1] = 0) then
    imageArray^[hloc + 1, vloc - 1] := stepIndex + 1;
160

    GetLine(hstart, vloc + vstart + 1, width, theLine);
if (theLine[hloc - 1] = 255) and
    (imageArray^[hloc - 1, vloc + 1] = 0) then
    imageArray^[hloc - 1, vloc + 1] := stepIndex + 1;
if (theLine[hloc] = 255) and
    (imageArray^[hloc, vloc + 1] = 0) then
    imageArray^[hloc, vloc + 1] := stepIndex + 1;
if (theLine[hloc + 1] = 255) and
    (imageArray^[hloc + 1, vloc + 1] = 0) then
    imageArray^[hloc + 1, vloc + 1] := stepIndex + 1;
170
    noProgress := FALSE;
end;
end;
hloc := width1;
if imageArray^[hloc, vloc] = stepIndex then begin
    GetLine(hstart, vloc + vstart, width, theLine);
if (theLine[hloc - 1] = 255) and
    (imageArray^[hloc - 1, vloc] = 0) then
    imageArray^[hloc - 1, vloc] := stepIndex + 1;
    GetLine(hstart, vloc + vstart - 1, width, theLine);
180
if (theLine[hloc - 1] = 255) and
    (imageArray^[hloc - 1, vloc - 1] = 0) then
    imageArray^[hloc - 1, vloc - 1] := stepIndex + 1;
if (theLine[hloc] = 255) and (imageArray^[hloc, vloc - 1] = 0) then
    imageArray^[hloc, vloc - 1] := stepIndex + 1;
    GetLine(hstart, vloc + vstart + 1, width, theLine);
if (theLine[hloc - 1] = 255) and
    (imageArray^[hloc - 1, vloc + 1] = 0) then
    imageArray^[hloc - 1, vloc + 1] := stepIndex + 1;
if (theLine[hloc] = 255) and (imageArray^[hloc, vloc + 1] = 0) then
190
    imageArray^[hloc, vloc + 1] := stepIndex + 1;
    noProgress := FALSE;
end;
end;

longtmp1 := stepIndex;
ShowMessage(concat('stepIndex=', long2str(longtmp1)));
if noProgress then begin
    DisposPtr(ptr(imageArray));
    PutMessage('Was not able to break through. ');
200
    exit(DoFindMinPath);
end;
stepIndex := stepIndex + 1;
vloc := height1;
for hloc := 0 to width1 do begin
    if imageArray^[hloc, vloc] <> 0 then begin
        BreakThrough := TRUE;
        ShowMessage('Breakthrough');
        breakpoint := hloc;
        hloc := width1;
210
    end;
end;
until BreakThrough;

for vloc := 0 to height1 do begin
    for hloc := 0 to width1 do begin
        theLine[hloc] := 0;
    end;
    PutLine(hstart, vloc + vstart, width, theLine);

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```

end;
220

vloc := height1;
hloc := breakPoint;
stepIndex := imageArray^[hloc, vloc] - 1;
imageArray^[hloc, vloc] := -1;

while vloc > 0 do begin
  xs := hloc - 1;
  if xs < 0 then
    xs := 0;
    230
  ys := vloc - 1;
  if ys < 0 then
    ys := 0;
  xe := hloc + 1;
  if xe > width1 then
    xe := width1;
  ye := vloc + 1;
  if ye > height1 then
    ye := height1;
  for y := ys to ye do begin
    240
    for x := xs to xe do begin
      if imageArray^[x, y] = stepIndex then begin
        imageArray^[x, y] := -1;
        stepIndex := stepIndex - 1;
        hloc := x;
        vloc := y;
        y := ye;
        x := xe;
        end;
        250
      end;
    end;
  end;

KillRoi;
for vloc := 0 to height1 do begin
  for hloc := 0 to width1 do begin
    if imageArray^[hloc, vloc] = -1 then
      theLine[hloc] := 255
    else
      theLine[hloc] := 0;
      260
    end;
  PutLine(hstart, vloc + vstart, width, theLine);
end;

UpdatePicWindow;

DisposPtr(ptr(imageArray));
ShowMessage('OK');
end
else begin
  270
  PutMessage('This is not a binary image!');
  exit(DoFindMinPath);
end;
end;
end;

```

A.5.2 Minimum-Path Dimension

```

procedure DoMinPathDim;
const
  NUM_BOX_SIZES = 25;
  INCLUDE_SECONDS = FALSE;
  WIDTH_TOTAL = 10;
  WIDTH_FLOAT = 8;

```

```

MAX_LENGTH = 1024;
type
ImageType = array[0..MAX_LENGTH, 0..MAX_LENGTH] of Boolean;
ImageTypePtr = ^ImageType;
var
imageArray: ImageTypePtr;
vstart, vend, hstart, hend, width, width1, height, height1, hloc, vloc,
      k, j, i, i9, dbmFirst, dbmLast: integer;
sizeIndex, x, y, neighbors, initPoints, pointIndex, pointLoc, dbcFirst,
      dbcLast: integer;
x0, y0, xStart, yStart, xEnd, yEnd, maxL, LARGEST_BOX_INDEX,
      FIRST_BOX_INDEX, LAST_BOX_INDEX: integer;
longtmp1, longtmp2, e2, occBox, minOccBox, configIdx, timeInSeconds,
      timeZero, dx, dy: longint;
dbint, dbdec1, dbdec2, sdbbint, sdbbdec1, sdbbdec2: longint;
templ, temp2, r1, r2, eSize, dbcmn, sdbbcmn: extended;
sx, sy, st2, db, ss, sxoss, t, intcp, sintcp, sddb, chi2, chi2Min,
      sigdat, dbmax, sdbbmax: extended;

theLine: LineType;
minPath: array[0..MAX_LENGTH, 0..1] of integer;
boxSizes: array[1..NUM_BOX_SIZES] of integer;
occupiedBoxes: array[1..NUM_BOX_SIZES] of longint;
lnBoxSizes, lnOccupiedBoxes, localSlope:
      array[1..NUM_BOX_SIZES] of extended;
smessage, smessage1, timeString, strtemp: Str255;
where: point;
reply: SFReply;
AutoSelectAll, doneAll: Boolean;
begin
with info^ do begin
if BinaryPic then begin
TextBufSize := 0;
boxSizes[1] := 512;
templ := 512.0;
for k := 2 to NUM_BOX_SIZES do begin
repeat
temp2 := 0.793700526 * templ;
j := round(temp2);
templ := temp2
until j <> boxSizes[k - 1];
boxSizes[k] := j;
end;

AutoSelectAll := not RoiShowing;
if AutoSelectAll then
SelectAll(false);

if roiType <> RectRoi then begin
PutMessage('I can only deal with a rectangular ROI!');
exit(DoMinPathDim);
end;

with RoiRect do begin
hend := right;
vend := bottom;
vstart := top;
hstart := left;
width := right - left;
height := bottom - top;
end;
width1 := width - 1;
height1 := height - 1;
if width > height then
maxL := width
else
maxL := height;

smessage := concat('Idx', tab, 'Size');

```

```

LARGEST_BOX_INDEX := 0;
repeat
  LARGEST_BOX_INDEX := LARGEST_BOX_INDEX + 1;
until boxSizes[LARGEST_BOX_INDEX] < maxL;

imageArray := ImageTypePtr(NewPtr(SizeOf(ImageType)));
if imageArray = nil then begin
  DisposPtr(ptr(imageArray));
  PutMessage('Insufficient memory');
  exit(DoMinPathDim);
end;
if (height > MAX_LENGTH) or (width > MAX_LENGTH) then begin
  longtmp1 := MAX_LENGTH;
  DisposPtr(ptr(imageArray));
  PutMessage(concat('Image width/length must be less than ',
    long2str(longtmp1), ' for dimension calculation!', cr,
    'Change MAX_LENGTH constant in source code for larger
    image.'));
  exit(DoMinPathDim);
end;

for vloc := 0 to height1 do begin
  GetLine(hStart, vloc + vstart, width, theLine);
  for hloc := 0 to width1 do begin
    if theLine[hloc] = 0 then
      imageArray^[hloc, vloc] := FALSE
    else
      imageArray^[hloc, vloc] := TRUE;
    end;
  end;
end;

initPoints := 0;
for vloc := 0 to height1 do begin
  for hloc := 0 to width1 do begin
    if imageArray^[hloc, vloc] then begin
      xStart := hloc - 1;
      if xStart < 0 then
        xStart := 0;
      yStart := vloc - 1;
      if yStart < 0 then
        yStart := 0;
      xEnd := hloc + 1;
      if xEnd > width1 then
        xEnd := width1;
      yEnd := vloc + 1;
      if yEnd > height1 then
        yEnd := height1;
      neighbors := -1;
      for y := yStart to yEnd do begin
        for x := xStart to xEnd do begin
          if imageArray^[x, y] then
            neighbors := neighbors + 1;
          end;
        end;
      if (neighbors < 1) or (neighbors > 2) then begin
        DisposPtr(ptr(imageArray));
        PutMessage('Minimum path must be a continuous
          skeletonized line!');
        exit(DoMinPathDim);
      end
      else if neighbors = 1 then
        if initPoints = 0 then begin
          minPath[0, 0] := hloc;
          minPath[0, 1] := vloc;
          initPoints := 1;
        end
      else begin
        initPoints := initPoints + 1;
      end;
    end;
  end;
end;

```



```

    if initPoints > 2 then begin
        DisposPtr(ptr(imageArray));
        PutMessage('Minimum path must be a continuous line!');
        exit(DoMinPathDim);
    end
end;
end;
end;
end;
150

pointIndex := 0;
repeat
doneAll := TRUE;
hloc := minPath[pointIndex, 0];
vloc := minPath[pointIndex, 1];
imageArray^[hloc, vloc] := FALSE;
xStart := hloc - 1;
if xStart < 0 then
xStart := 0;
160
yStart := vloc - 1;
if yStart < 0 then
yStart := 0;
xEnd := hloc + 1;
if xEnd > width1 then
xEnd := width1;
yEnd := vloc + 1;
if yEnd > height1 then
yEnd := height1;
170
for y := yStart to yEnd do begin
for x := xStart to xEnd do begin
if imageArray^[x, y] then begin
doneAll := FALSE;
pointIndex := pointIndex + 1;
minPath[pointIndex, 0] := x;
minPath[pointIndex, 1] := y;
y := yEnd;
x := xEnd;
180
end;
end;
end;
until doneAll;

longtmp1 := pointIndex;
ShowMessage(concat('Points: ', long2str(longtmp1)));

for k := LARGEST_BOX_INDEX to NUM_BOX_SIZES do begin
longtmp1 := k;
longtmp2 := boxSizes[k];
190
if k < 10 then
smessage := concat(smessage, cr, '0', long2str(longtmp1),
tab, long2str(longtmp2))
else
smessage := concat(smessage, cr, long2str(longtmp1), tab,
long2str(longtmp2));
end;

smessage := '';
smessage1 := '';
200

PutString(concat('Number', tab, 'Box Size', tab, 'Occupied Boxes',
tab, 'ln [Box Size]', tab, 'ln [Occupied Boxes]',
tab, 'Local Slope', cr));

GetDateTime(timeZero);
for sizeIndex := LARGEST_BOX_INDEX to NUM_BOX_SIZES do begin
eSize := 1.0 * boxSizes[sizeIndex];
if CommandPeriod then begin
210
beep;

```

```

DisposPtr(ptr(imageArray));
exit(DoMinPathDim);
end;

minOccBox := MAX_LENGTH + 1;

for configIdx := 0 to pointIndex do begin
  occBox := 0;
  pointLoc := configIdx;
  220

  for i := configIdx downto 0 do begin
    dx := minPath[i, 0] - minPath[pointLoc, 0];
    dy := minPath[i, 1] - minPath[pointLoc, 1];
    r1 := sqrt(dx * dx + dy * dy);
    if r1 >= eSize then begin
      dx := minPath[i + 1, 0] - minPath[pointLoc, 0];
      dy := minPath[i + 1, 1] - minPath[pointLoc, 1];
      r2 := sqrt(dx * dx + dy * dy);
      if (r1 - eSize) < (eSize - r2) then begin
        pointLoc := i;
        occBox := occBox + 1;
        230
      end
    else begin
      pointLoc := i + 1;
      i := i + 1;
      occBox := occBox + 1;
    end
  end;
end;
if pointLoc > 0 then
  occBox := occBox + 1;
  240

pointLoc := configIdx;
for i := configIdx to pointIndex do begin
  dx := minPath[i, 0] - minPath[pointLoc, 0];
  dy := minPath[i, 1] - minPath[pointLoc, 1];
  r1 := sqrt(dx * dx + dy * dy);
  if r1 >= eSize then begin
    dx := minPath[i - 1, 0] - minPath[pointLoc, 0];
    dy := minPath[i - 1, 1] - minPath[pointLoc, 1];
    r2 := sqrt(dx * dx + dy * dy);
    if (r1 - eSize) < (eSize - r2) then begin
      pointLoc := i;
      occBox := occBox + 1;
      250
    end
  else begin
    pointLoc := i - 1;
    i := i - 1;
    occBox := occBox + 1;
  end
end;
  260
end;
if pointLoc < pointIndex then
  occBox := occBox + 1;

if occBox < minOccBox then
  minOccBox := occBox;
end;

occupiedBoxes[sizeIndex] := minOccBox;
  270
GetDate(timeInSeconds);
timeInSeconds := timeInSeconds - timeZero;
IUTimeString(timeInSeconds, INCLUDE_SECONDS, timeString);
longtmp1 := boxSizes[sizeIndex];
longtmp2 := occupiedBoxes[sizeIndex];
smessage := concat(smessage1, cr, long2str(longtmp1),
  tab, long2str(longtmp2));
ShowMessage(concat('Sz', tab, 'Occupied', smessage, cr,

```

```

                'Time: ', timeString));
smessage1 := smessage;
smessage := concat(smessage, cr, 'Time: ', timeString);
lnBoxSizes[sizeIndex] := Ln(boxSizes[sizeIndex]);
lnOccupiedBoxes[sizeIndex] := Ln(occupiedBoxes[sizeIndex]);
end;

for sizeIndex := LARGEST_BOX_INDEX to NUM_BOX_SIZES do begin
if (sizeIndex > LARGEST_BOX_INDEX + 1) and
(sizeIndex < NUM_BOX_SIZES - 1) then begin
    sx := 0.0;
    sy := 0.0;
    st2 := 0.0;
    db := 0.0;
    for i9 := sizeIndex - 2 to sizeIndex + 2 do begin
        sx := sx + lnBoxSizes[i9];
        sy := sy + lnOccupiedBoxes[i9];
    end;
    ss := 5.0; {number of points to calculate local slope }
    sxoss := sx / ss;
    for i9 := sizeIndex - 2 to sizeIndex + 2 do begin
        t := lnBoxSizes[i9] - sxoss;
        st2 := st2 + t * t;
        db := db + t * lnOccupiedBoxes[i9];
    end;
    db := 0.0 - db / st2;
    localSlope[sizeIndex] := db;
end
else
    localSlope[sizeIndex] := 0.0;

    longtmp1 := sizeIndex;
    strtemp := long2str(longtmp1);
    PutString(strtemp);
    PutChar(tab);
    longtmp1 := boxSizes[sizeIndex];
    strtemp := long2str(longtmp1);
    PutString(strtemp);
    PutChar(tab);
    longtmp2 := occupiedBoxes[sizeIndex];
    strtemp := long2str(longtmp2);
    PutString(strtemp);
    PutChar(tab);
    PutReal(lnBoxSizes[sizeIndex], WIDTH_TOTAL, WIDTH_FLOAT);
    PutChar(tab);
    PutReal(lnOccupiedBoxes[sizeIndex], WIDTH_TOTAL, WIDTH_FLOAT);
    PutChar(tab);
    PutReal(localSlope[sizeIndex], WIDTH_TOTAL, WIDTH_FLOAT);
    PutChar(cr);
end;

where.v := 100;
where.h := 100;
SFPutFile(where, 'Save the results as?', concat(title, '.box'),
nil, reply);
if reply.good then
with reply do
    SaveAsText(fname, vRefnum);

TextBufSize := 0;
PutString(concat('No. of pts.', tab, '1st box no.', tab, 'Last box no.',
tab, '1st box size', tab, 'Last box size', tab, 'Box
Dimension', tab, 'Std Error', cr));
smessage1 := concat('Pts', tab, 'Dbox');

for j := 7 to NUM_BOX_SIZES - LARGEST_BOX_INDEX + 1 do begin
chi2Min := 999999999.9;
dbmax := 0.0;

```

```

for LAST_BOX_INDEX := NUM_BOX_SIZES downto
    LARGEST_BOX_INDEX + j - 1 do begin
    FIRST_BOX_INDEX := LAST_BOX_INDEX - j + 1;
    sx := 0.0;
    sy := 0.0;
    st2 := 0.0;
    db := 0.0;
    for i := FIRST_BOX_INDEX to LAST_BOX_INDEX do begin
        sx := sx + lnBoxSizes[i];
        sy := sy + lnOccupiedBoxes[i];
    end;
    ss := LAST_BOX_INDEX - FIRST_BOX_INDEX + 1.0;
    sxoss := sx / ss;

    for i := FIRST_BOX_INDEX to LAST_BOX_INDEX do begin
        t := lnBoxSizes[i] - sxoss;
        st2 := st2 + t * t;
        db := db + t * lnOccupiedBoxes[i];
    end;
    db := db / st2;
    intcp := (sy - sx * db) / ss;
    sintcp := Sqrt((1.0 + sx * sx / (ss * st2)) / ss);
    sddb := Sqrt(1.0 / st2);
    chi2 := 0.0;

    for i := FIRST_BOX_INDEX to LAST_BOX_INDEX do begin
        temp1 := lnOccupiedBoxes[i] - intcp - db * lnBoxSizes[i];
        chi2 := chi2 + temp1 * temp1;
    end;
    sigdat := Sqrt(chi2 / (ss - 2.0));
    sintcp := sintcp * sigdat;
    sddb := sddb * sigdat;
    db := 0.0 - db;
    if db > dbmax then begin
        dbmax := db;
        sddbmax := sddb;
        dbmFirst := FIRST_BOX_INDEX;
        dbmLast := LAST_BOX_INDEX;
    end;
    if chi2Min > chi2 then begin
        chi2Min := chi2;
        dbcmn := db;
        sddbcmn := sddb;
        dbcFirst := FIRST_BOX_INDEX;
        dbcLast := LAST_BOX_INDEX;
    end;
end;

    longtmp1 := j;
    strtemp := concat('MX ', long2str(longtmp1));
    PutString(strtemp);
    PutChar(tab);
    longtmp1 := dbmFirst;
    strtemp := long2str(longtmp1);
    PutString(strtemp);
    PutChar(tab);
    longtmp1 := dbmLast;
    strtemp := long2str(longtmp1);
    PutString(strtemp);
    PutChar(tab);
    longtmp1 := boxSizes[dbmFirst];
    strtemp := long2str(longtmp1);
    PutString(strtemp);
    PutChar(tab);
    longtmp2 := boxSizes[dbmLast];
    strtemp := long2str(longtmp2);
    PutString(strtemp);
    PutChar(tab);

```

```

PutReal(dbmax, WIDTH_TOTAL, WIDTH_FLOAT);
PutChar(tab);
PutReal(sddbmax, WIDTH_TOTAL, WIDTH_FLOAT);
PutChar(cr);

longtmp1 := j;
strtemp := concat('BS ', long2str(longtmp1));
PutString(strtemp);
PutChar(tab);
if j < 10 then
  strtemp := concat('0', long2str(longtmp1))
else
  strtemp := long2str(longtmp1);
  smessage1 := concat(smessage1, cr, strtemp);
  longtmp1 := dbcFirst;
  strtemp := long2str(longtmp1);
  PutString(strtemp);
  PutChar(tab);
  longtmp1 := dbcLast;
  strtemp := long2str(longtmp1);
  PutString(strtemp);
  PutChar(tab);
  longtmp1 := boxSizes[dbcFirst];
  strtemp := long2str(longtmp1);
  PutString(strtemp);
  PutChar(tab);
  longtmp2 := boxSizes[dbcLast];
  strtemp := long2str(longtmp2);
  PutString(strtemp);
  PutChar(tab);
  PutReal(dbcmn, WIDTH_TOTAL, WIDTH_FLOAT);
  PutChar(tab);
  PutReal(sddbcmn, WIDTH_TOTAL, WIDTH_FLOAT);
  PutChar(cr);

  dbint := trunc(dbcmn);
  dbdec1 := trunc(dbcmn * 10.0) - dbint * 10;
  dbdec2 := trunc(dbcmn * 100.0) - dbint * 100 - dbdec1 * 10;
  sddbint := trunc(sddbcmn);
  sddbdec1 := trunc(sddbcmn * 10.0) - sddbint * 10;
  sddbdec2 := trunc(sddbcmn * 100.0) - sddbint * 100 - sddbdec1 * 10;
  smessage := concat(smessage1, tab, long2str(dbint), '.',
    long2str(dbdec1), long2str(dbdec2), '±',
    long2str(sddbint), '.', long2str(sddbdec1),
    long2str(sddbdec2));
  ShowMessage(smessage);
  smessage1 := smessage;
end;

where.v := 100;
where.h := 100;
SFPutFile(where, 'Save the results as?', concat(title, '.slopes'),
  nil, reply);
if reply.good then
  with reply do
    SaveAsText(fname, vRefnum);

  DisposPtr(ptr(imageArray));

end
else begin
  PutMessage('This is not a binary image!');
  exit(DoMinPathDim);
end;
end;
end;

```

A.6 2-D Growth Modeling Program

```

PROGRAM DoModelTime

REAL*4 RNUNF

*   Assign parameters:
INTEGER*4 AUTO_ITERATIONS,MAX_LENGTH,MAX_LENGTH1
PARAMETER (AUTO_ITERATIONS=100,MAX_LENGTH=128,MAX_LENGTH1=127)
INTEGER*4 MAX_TIME,MAX_NUM_PARTICLES
PARAMETER (MAX_TIME=1000000,MAX_NUM_PARTICLES=100000)
INTEGER*4 NO_PROD_RADIUS                                10
PARAMETER (NO_PROD_RADIUS=10)
INTEGER*4 NUM_BOX_SIZES
PARAMETER (NUM_BOX_SIZES=25)
INTEGER*4 MAX_PATH_LENGTH
PARAMETER (MAX_PATH_LENGTH=1000)

*   Declare image-size variables:
INTEGER*4 width,width1,width2,height,height1,height2
REAL*4 imageArea                                        20

*   Declare multi-purpose variables:
INTEGER*4 vloc,hloc,xTemp,yTemp,xNo,yNo,yT,xT
INTEGER*4 k,i,j
INTEGER*4 longtmp(0:3)
LOGICAL*4 bTemp1,bTemp2
REAL*4 numerator,denominator
INTEGER*4 compTime,tArray(1:3)

*   Declare model parameters:
INTEGER*4 halfLife,growthWaitUnits,intL                30
INTEGER*4 numGroups,growthThreshold,releaseThreshold
LOGICAL*4 homogeneousSub,homogeneousDif,centerSeed
REAL*4 productionRate,stickingProb,extraRelease,growthRange
REAL*4 releaseAtGrowthSite,tau,fintL
LOGICAL*4 waitUnit,uniformParticleDist

*   Declare model variables:
INTEGER*4 xCntr,yCntr,release,numRelease,autoCounter
INTEGER*4 timeUnits,hitUnits,numDecayed,numParticles,occNeighbors
INTEGER*4 totalTime,highestParticle,numNew,emptyParticle  40
INTEGER*4 totalParts,tissueParts,extraParticles,growthSites
REAL*4 decayProb,weakest,frac
LOGICAL*4 BreakThrough,keepWaiting,foundEmpty
INTEGER*4 furthest,bestDistance,bestMass

*   Declare final image variables:
INTEGER*4 pGroupSize,pAge

*   Declare arrays:
INTEGER*4 imageArray(0:MAX_LENGTH1,0:MAX_LENGTH1)      50
REAL*4 strengthArrayDif(0:MAX_LENGTH1,0:MAX_LENGTH1)
REAL*4 strengthArraySub(0:MAX_LENGTH1,0:MAX_LENGTH1)
INTEGER*4 hitArray(0:MAX_LENGTH1,0:MAX_LENGTH1)
INTEGER*4 xParticle(1:MAX_NUM_PARTICLES)
INTEGER*4 yParticle(1:MAX_NUM_PARTICLES)
INTEGER*4 ageParticle(1:MAX_NUM_PARTICLES)
LOGICAL*4 activeParticle(1:MAX_NUM_PARTICLES)

*   Declare result variables:
INTEGER*4 bestImage(0:MAX_LENGTH1,0:MAX_LENGTH1)      60
INTEGER*4 heavyImage(0:MAX_LENGTH1,0:MAX_LENGTH1)
REAL*4 dimList(0:AUTO_ITERATIONS)
REAL*4 sdDimList(0:AUTO_ITERATIONS)
REAL*4 mpdimList(0:AUTO_ITERATIONS)

```

```

REAL*4 sdMpdimList(0:AUTO_ITERATIONS)
REAL*4 timeMassList(0:AUTO_ITERATIONS)
REAL*4 tissueEffList(0:AUTO_ITERATIONS)
REAL*4 totalEffList(0:AUTO_ITERATIONS)
INTEGER*4 timeList(0:AUTO_ITERATIONS),massList(0:AUTO_ITERATIONS)
INTEGER*4 tissuePartList(0:AUTO_ITERATIONS)
INTEGER*4 totalPartList(0:AUTO_ITERATIONS)
INTEGER*4 decayPartList(0:AUTO_ITERATIONS)
REAL*4 timeMassAvg,totalEffAvg,tissueEffAvg,timeAvg,massAvg
REAL*4 tissuePartAvg,totalPartAvg,decayPartAvg
REAL*4 timeMassSD,totalEffSD,tissueEffSD,timeSD,massSD
REAL*4 tissuePartSD,totalPartSD,decayPartSD
REAL*4 mpdim,sdmpdim

*   Declare mass--radius variables:
INTEGER*4 sizeIndex,xStart,yStart,xEnd,yEnd,mass,xc,yc
INTEGER*4 xr,yr,minLength
INTEGER*4 LARGEST_BOX_INDEX,FIRST_BOX_INDEX,LAST_BOX_INDEX
REAL*4 temp1,temp2
REAL*4 sx,sy,st2,db,ss,sxoss,t,sddb,chi2,sigdat,intcp
INTEGER*4 boxSizes(1:NUM_BOX_SIZES),totalMass(1:NUM_BOX_SIZES)
REAL*4 lnBoxSizes(1:NUM_BOX_SIZES),lnTotalMass(1:NUM_BOX_SIZES)

*   Declare minimum path variables:
LOGICAL*4 noProgress
INTEGER*4 minPathArray(0:MAX_LENGTH1,0:MAX_LENGTH1)
INTEGER*4 stepIndex,vstart,vend,hstart,hend
INTEGER*4 breakPoint,x,y,xs,ys
INTEGER*4 minPath(0:MAX_PATH_LENGTH,0:1)
INTEGER*4 pointIndex,pointLoc,occBox,configIdx
INTEGER*4 dx,dy
REAL*4 eSize,r1

CALL ITIME(tArray)
compTime=tArray(3)+tArray(2)*60+tArray(1)*3600

*   Initialize parameters:
intL=32768
fintL=32768.0

*   Initialize size variables:
width = MAX_LENGTH
width1 = width - 1
width2 = width - 2
height = MAX_LENGTH
height1 = height - 1
height2 = height - 2

*   Initialize dimension measurement parameters:
boxSizes(1) = 512
temp1 = 512.0
DO 5 k=2,NUM_BOX_SIZES
4  temp2 = 0.793700526*temp1
   j = NINT(temp2)
   temp1 = temp2
   IF (j.EQ.boxSizes(k-1)) GO TO 4
   boxSizes(k) = j
5  CONTINUE

*   Assign Parameters:
homogeneousSub = .TRUE.
homogeneousDif = .TRUE.
centerSeed = .TRUE.
waitUnit = .TRUE.
growthWaitUnits = 10
halfLife = 1000000
tau = FLOAT(halfLife)/ALOG(2.0)

```

```

numGroups = 250
uniformParticleDist = .FALSE.
imageArea = FLOAT(height)*FLOAT(width)
productionRate = 0.000056234133
stickingProb = 1.0
extraRelease = 0.0
releaseAtGrowthSite = 0.0
growthThreshold = 1
releaseThreshold = 1
growthRange = 1.0
140

OPEN (UNIT=15,FILE='Model.Specs',STATUS='NEW')
WRITE (15,2200) 'Model Specifications:'
IF (homogeneousSub) THEN
  WRITE (15,2200) 'Homogeneous Substrate'
ELSE
  WRITE (15,2200) 'Inhomogeneous Substrate'
ENDIF
IF (homogeneousDif) THEN
  WRITE (15,2200) 'Homogeneous Diffusion'
ELSE
  WRITE (15,2200) 'Inhomogeneous Diffusion'
ENDIF
IF (centerSeed) THEN
  WRITE (15,2200) 'Center Seed'
ELSE
  WRITE (15,2200) 'Multiple Seeds'
ENDIF
IF (waitUnit) THEN
  WRITE (15,2200) 'Wait Unit: TIME'
ELSE
  WRITE (15,2200) 'Wait Unit: HIT'
ENDIF
WRITE (15,2210) 'Growth Wait Units :',growthWaitUnits
WRITE (15,2210) 'Particle Half-life:',halfLife
IF (uniformParticleDist) THEN
  WRITE (15,2200) 'Uniform particle origin'
ELSE
  WRITE (15,2200) 'Particle origin beyond network'
ENDIF
WRITE (15,2220) 'Production Rate: ',productionRate,
C 'particles/pixel*time'
WRITE (15,2230) 'Interaction Probability:',stickingProb
WRITE (15,2230) 'Extra release per hit:',extraRelease
WRITE (15,2230) 'Extra release at growth site:',
C releaseAtGrowthSite
WRITE (15,2210) 'Growth threshold:',growthThreshold
WRITE (15,2210) 'Extra release threshold:',releaseThreshold
WRITE (15,2230) 'Growth Range: 0.0 -',growthRange
170
CLOSE (UNIT=15)

OPEN (UNIT=16,FILE='Model.Data',STATUS='NEW')
WRITE (16,2270)
C ' No Dm-r Dmp T/M tis-E',
C ' tot-E Time Mass Tis Tot Dec'

bestDistance = MAX_LENGTH/2
bestMass = 0
190

* Seeding code:
CALL RNOPT(6)
CALL RNSET(0)
* End of seeding code

* Initialize iteration counter:
autoCounter = 0
10 autoCounter = autoCounter + 1
200

```



```

* Assign growth substrate strengths:
  IF (.NOT.homogeneousSub) THEN
    PRINT *,'Generating random substrate strengths...'
    DO 110 vloc=0,height1
      DO 100 hloc=0,width1
        strengthArraySub(hloc,vloc)= RNUNF()
100    CONTINUE
110    CONTINUE
    PRINT *,'Random growth substrate generated.'
    ELSE
      DO 130 vloc=0,height1
        DO 120 hloc=0,width1
          strengthArraySub(hloc,vloc)=0.5
120    CONTINUE
130    CONTINUE
    ENDIF
220

* Assign diffusion substrate strengths:
  IF (.NOT.homogeneousDif) THEN
    PRINT *,'Generating random diffusion strengths...'
    DO 160 vloc=0,height1
      DO 150 hloc=0,width1
        strengthArrayDif(hloc,vloc)= RNUNF()
150    CONTINUE
160    CONTINUE
    PRINT *,'Random diffusion substrate generated.'
    ENDIF
230

* Initialize model variables:

  DO 200 i=1,MAX_NUM_PARTICLES
    activeParticle(i)=.FALSE.
200 CONTINUE

  BreakThrough = .FALSE.
  numDecayed = 0
  totalTime = 0
  totalParts = 0
  tissueParts = 0
  extraParticles = 0
240

  DO 220 vloc=0,height1
    DO 210 hloc=0,width1
      imageArray(hloc,vloc)=0
210 CONTINUE
220 CONTINUE
250

  IF (centerSeed) THEN
    yCntr = height/2
    xCntr = width/2
    numParticles = 1
    imageArray(xCntr,yCntr)=numParticles

  IF (.NOT.uniformParticleDist) THEN
    DO 250 yNo=-NO_PROD_RADIUS,NO_PROD_RADIUS
      yT = yNo + yCntr
      IF (yT.GT.height1) yT=yT-height
      IF (yT.LT.0) yT=height-yT
      DO 240 xNo=-NO_PROD_RADIUS,NO_PROD_RADIUS
        xT = xNo + xCntr
        IF (xT.GT.width1) xT=xT-width
        IF (xT.LT.0) xT=width-xT
        IF (SQRT(FLOAT(xNo*xNo+yNo*yNo)).LT.NO_PROD_RADIUS) THEN
          IF (imageArray(xT,yT).EQ.0) imageArray(xT,yT)=-1
260

```

```

    ENDIF
240 CONTINUE
250 CONTINUE
    ENDIF
    ELSE
    PRINT *,'Only center-seed option is available!'
    STOP
    ENDIF

* ##### Main loop until BreakThrough #####
DO 1000 WHILE (.NOT.BreakThrough)
    keepWaiting=.TRUE.
    timeUnits=0
    hitUnits=0

    DO 310 vloc=0,height1
    DO 300 hloc=0,width1
    hitArray(hloc,vloc)=0
300 CONTINUE
310 CONTINUE

    highestParticle=0
    DO 320 i=1,MAX_NUM_PARTICLES
    IF (activeParticle(i)) highestParticle=i
320 CONTINUE

* Loop waiting for time for growth:
DO 700 WHILE (keepWaiting)

    timeUnits=timeUnits+1
    totalTime=totalTime+1

* Advance existing particles:
DO 400 i=1,highestParticle
    IF (activeParticle(i)) THEN

        ageParticle(i)=ageParticle(i)+1

* Takes into account only the case where homogeneousDif=TRUE:
k=AINT(4.0*RNUNF()+1)
GO TO (350,360,370,380), k
350 xTemp = xParticle(i) + 1
    yTemp = yParticle(i)
    IF (xTemp.EQ.width) xTemp=0
    GO TO 390
360 xTemp = xParticle(i) - 1
    yTemp = yParticle(i)
    IF (xTemp.EQ.-1) xTemp=width1
    GO TO 390
370 yTemp = yParticle(i) - 1
    xTemp = xParticle(i)
    IF (yTemp.EQ.-1) yTemp=height1
    GO TO 390
380 yTemp = yParticle(i) + 1
    xTemp = xParticle(i)
    IF (yTemp.EQ.height) yTemp=0
390 IF (imageArray(xTemp,yTemp).LE.0) THEN
    xParticle(i)=xTemp
    yParticle(i)=yTemp
    ENDIF
    ENDIF
400 CONTINUE

* Produce new particles:

numNew=AINT(productionRate*imageArea)
frac=productionRate*imageArea-1.0*FLOAT(numNew)

```

```

IF (RNUNF().LT.frac) numNew=numNew+1
emptyParticle = 1
DO 460 i=1,numNew
  xTemp = NINT(RNUNF()*width1)
  yTemp = NINT(RNUNF()*height1)
  IF (imageArray(xTemp,yTemp).EQ.0) THEN
    foundEmpty = .FALSE.
    k = emptyParticle - 1
    DO 450 WHILE (k.LT.MAX_NUM_PARTICLES)
      k = k + 1
      IF (.NOT.activeParticle(k)) THEN
        emptyParticle = k
        foundEmpty = .TRUE.
        k = MAX_NUM_PARTICLES
      ENDIF
    END DO
  END DO

  IF (.NOT.foundEmpty) THEN
    PRINT *,'Too Many Particles!'
    STOP
  ENDIF

  tissueParts = tissueParts + 1
  totalParts = totalParts + 1
  activeParticle(emptyParticle)=.TRUE.
  xParticle(emptyParticle)=xTemp
  yParticle(emptyParticle)=yTemp
  ageParticle(emptyParticle)=1
  IF (emptyParticle.GT.highestParticle)
    C highestParticle=emptyParticle
  ENDIF
CONTINUE

*   Degrade old particles:

DO 500 i=1,highestParticle
  IF (activeParticle(i)) THEN
    decayProb = EXP(-FLOAT(ageParticle(i))/tau)/tau
    IF (RNUNF().LT.decayProb) THEN
      numDecayed = numDecayed + 1
      activeParticle(i)=.FALSE.
    ENDIF
  ENDIF
CONTINUE

*   Mark hits:
DO 600 i=1,highestParticle
  IF (activeParticle(i)) THEN
    xTemp = xParticle(i)
    yTemp = yParticle(i)
    bTemp1 = ((xTemp.LT.width1).AND.(yTemp.LT.height1))
    bTemp2 = ((xTemp.GT.0).AND.(yTemp.GT.0))
    IF (bTemp1.AND.bTemp2) THEN
      longtmp(0)=AINT(FLOAT(intL-1+imageArray((xTemp+1),yTemp)))/
        fintL
      C longtmp(1)=AINT(FLOAT(intL-1+imageArray((xTemp-1),yTemp)))/
        fintL
      C longtmp(2)=AINT(FLOAT(intL-1+imageArray(xTemp,(yTemp+1)))/
        fintL)
      C longtmp(3)=AINT(FLOAT(intL-1+imageArray(xTemp,(yTemp-1)))/
        fintL)
      occNeighbors=longtmp(0)+longtmp(1)+longtmp(2)+longtmp(3)
      IF (occNeighbors.GT.0) THEN
        IF (RNUNF().LT.(stickingProb*FLOAT(occNeighbors))) THEN
          activeParticle(i)=.FALSE.
          hitArray(xTemp,yTemp)=hitArray(xTemp,yTemp)+1
          hitUnits = hitUnits + 1
        ENDIF
      ENDIF
    ENDIF
  ENDIF

```

```

IF (MOD(hitArray(xTemp,yTemp),releaseThreshold).EQ.0) THEN
  emptyParticle = 1
  numRelease = AINT(extraRelease)
  frac = extraRelease - FLOAT(numRelease)
  IF (RNUNF().LT.frac) numRelease=numRelease+1
  DO 580 release=1,numRelease
    foundEmpty=.FALSE.
    k=emptyParticle - 1
    DO 540 WHILE (k.LT.i)
      k = k + 1
      IF (.NOT.activeParticle(k)) THEN
        emptyParticle = k
        foundEmpty = .TRUE.
        k = i
      ENDIF
    END DO
    IF (.NOT.foundEmpty) THEN
      k=highestParticle
      DO 560 WHILE (k.LT.MAX_NUM_PARTICLES)
        k = k + 1
        IF (.NOT.activeParticle(k)) THEN
          emptyParticle = k
          foundEmpty = .TRUE.
          k = MAX_NUM_PARTICLES
        ENDIF
      END DO
      IF (.NOT.foundEmpty) THEN
        PRINT *,'Too Many Particles!'
        STOP
      ENDIF
      extraParticles = extraParticles + 1
      totalParts = totalParts + 1
      activeParticle(emptyParticle) = .TRUE.
      xParticle(emptyParticle) = xTemp
      yParticle(emptyParticle) = yTemp
      ageParticle(emptyParticle) = 1
    ENDIF
  END DO
  ENDIF
  ENDIF
  ENDIF
  ENDIF
600 CONTINUE

*   Check if time for growth:
    IF (waitUnit) THEN
      IF (timeUnits.EQ.growthWaitUnits) keepWaiting=.FALSE.
    ELSE
      IF (hitUnits.GE.growthWaitUnits) keepWaiting=.FALSE.
    ENDIF

    IF (totalTime.EQ.MAX_TIME) THEN
      PRINT *,'Time exceeded maximum'
      STOP
    ENDIF

700 END DO
*   End of loop waiting for growth event time

*   Begin growth:
    IF (hitUnits.GT.0) THEN
      growthSites = 0
      weakest = 1.0
      DO 720 vloc=0,height1
        DO 710 hloc=0,width1
          IF (hitArray(hloc,vloc).GE.growthThreshold) THEN

```

```

    IF (strengthArraySub(hloc,vloc).LT.weakest) THEN
      weakest=strengthArraySub(hloc,vloc)
    ENDIF
  ENDIF
710 CONTINUE
720 CONTINUE

DO 900 vloc=0,height1
DO 890 hloc=0,width1
  IF (hitArray(hloc,vloc).GE.growthThreshold) THEN
    bTemp1=(strengthArraySub(hloc,vloc).LE.growthRange)
    bTemp2=(strengthArraySub(hloc,vloc).EQ.weakest)
    IF (bTemp1.OR.bTemp2) THEN

      xTemp = hloc
      yTemp = vloc
      growthSites = growthSites + 1
      numParticles = numParticles + 1
      imageArray(xTemp,yTemp) = numParticles
      bTemp1=((xTemp.EQ.width2).OR.(xTemp.EQ.1))
      bTemp2=((yTemp.EQ.height2).OR.(yTemp.EQ.1))
      IF (bTemp1.OR.bTemp2) BreakThrough=.TRUE.

*      Mark no production area:
      IF (.NOT.uniformParticleDist) THEN
        DO 760 yNo=-NO_PROD_RADIUS,NO_PROD_RADIUS
          yT = yNo + yTemp
          IF (yT.GT.height1) yT=yT-height
          IF (yT.LT.0) yT=height-yT
          DO 750 xNo=-NO_PROD_RADIUS,NO_PROD_RADIUS
            xT = xNo + xTemp
            IF (xT.GT.width1) xT=xT-width
            IF (xT.LT.0) xT=width-xT
            IF (SQRT(FLOAT(xNo*xNo+yNo*yNo)).LE.NO_PROD_RADIUS) THEN
              IF (imageArray(xT,yT).EQ.0) imageArray(xT,yT)=-1
            ENDIF
750 CONTINUE
760 CONTINUE
          ENDIF
*      End marking no production area

*      Remove additional particles currently residing on growth site:
      DO 770 i=1,highestParticle
        IF (activeParticle(i)) THEN
          IF ((xParticle(i).EQ.xTemp).AND.(yParticle(i).EQ.yTemp))
            C activeParticle(i)=.FALSE.
          ENDIF
770 CONTINUE
*      End removal

*      Release additional particles to nearest neighbors of growth site:
      DO 780 i=0,3
        longtmp(i)=0
780 CONTINUE
        IF (imageArray((xTemp+1),yTemp).LE.0) longtmp(0)=1
        IF (imageArray((xTemp-1),yTemp).LE.0) longtmp(1)=1
        IF (imageArray(xTemp,(yTemp+1)).LE.0) longtmp(2)=1
        IF (imageArray(xTemp,(yTemp-1)).LE.0) longtmp(3)=1
        numRelease = AINT(releaseAtGrowthSite)
        frac = releaseAtGrowthSite - FLOAT(numRelease)
        IF (RNUNF().LT.frac) numRelease=numRelease+1
        bTemp1=((longtmp(0)+longtmp(1)+longtmp(2)+longtmp(3)).EQ.0)
        IF (bTemp1) numRelease=0
        release = 0
        DO 870 WHILE (release.LT.numRelease)
*      Takes into account only the case where homogeneousDif=TRUE
        release = release + 1
        k = AINT(4.0*RNUNF())

```

```

      IF (k.EQ.4) k=3
      IF (longtmp(k).NE.1) THEN
        release=release-1
      ELSE
        foundEmpty = .FALSE.
        i = 0
        DO 810 WHILE (i.LT.MAX_NUM_PARTICLES)
          i = i + 1
          IF (.NOT.activeParticle(i)) THEN
            emptyParticle = i
            foundEmpty = .TRUE.
            i = MAX_NUM_PARTICLES
          ENDIF
810        END DO
          IF (foundEmpty) THEN
            extraParticles = extraParticles + 1
            totalParts = totalParts + 1
            activeParticle(emptyParticle) = .TRUE.
            ageParticle(emptyParticle) = 1
            k=k+1
            GO TO (820,830,840,850), k
820          xParticle(emptyParticle) = xTemp + 1
            yParticle(emptyParticle) = yTemp
            GO TO 860
830          xParticle(emptyParticle) = xTemp - 1
            yParticle(emptyParticle) = yTemp
            GO TO 860
840          xParticle(emptyParticle) = xTemp
            yParticle(emptyParticle) = yTemp + 1
            GO TO 860
850          xParticle(emptyParticle) = xTemp
            yParticle(emptyParticle) = yTemp - 1
            GO TO 860
860          ENDIF
          ENDIF
870        END DO
      *      End release

      ENDIF
      ENDIF
890    CONTINUE
900    CONTINUE
      *      Print '(1X,A,I5,4X,A,I8,4X,A,I6,4X,A,I5)',
      *      C      'Counter:',autoCounter,'Time:',totalTime,'Hits:',
      *      C      hitUnits,'Growth Sites:',growthSites
      ENDIF
      *      End Growth

1000 END DO

      PRINT *, 'Breakthrough'

      *      Find center of mass:
      xc = 0
      yc = 0
      DO 1050 vloc=0,height1
        DO 1040 hloc=0,width1
          IF (imageArray(hloc,vloc).GT.0) THEN
            xc = xc + hloc
            yc = yc + vloc
          ENDIF
1040        CONTINUE
1050      CONTINUE
      xc = NINT(FLOAT(xc)/FLOAT(numParticles))
      yc = NINT(FLOAT(yc)/FLOAT(numParticles))

      minLength=MIN(xc,yc,(MAX_LENGTH-yc-1),(MAX_LENGTH-xc-1))/2

```

```

DO 1110 i=0,minLength
DO 1100 vloc=0-i,i
DO 1090 hloc=0-i,i
IF (imageArray((xc+hloc),(yc+vloc)).GT.0) THEN
xc = xc + hloc
yc = yc + vloc
GO TO 1120
ENDIF
1090 CONTINUE
1100 CONTINUE
1110 CONTINUE
PRINT *, 'Could not find occupied pixel around center of mass'
STOP

1120 minLength=MIN(xc,yc,(MAX_LENGTH-xc-1),(MAX_LENGTH-yc-1))/2
LARGEST_BOX_INDEX = 1
DO WHILE (boxSizes(LARGEST_BOX_INDEX).GE.minLength)
LARGEST_BOX_INDEX = LARGEST_BOX_INDEX + 1
END DO

pGroupSize = AINT(FLOAT(numParticles)/FLOAT(numGroups))+1
DO 1140 vloc=0,height1
DO 1130 hloc=0,width1
pAge=imageArray(hloc,vloc)
IF (pAge.GT.0) THEN
imageArray(hloc,vloc)=254-AINT(FLOAT(pAge)/FLOAT(pGroupSize))
ELSE
imageArray(hloc,vloc)=0
ENDIF
1130 CONTINUE
1140 CONTINUE

PRINT *, 'Find best images'

furthest = 0
DO 1160 vloc=0,height1
DO 1150 hloc=0,width1
IF (imageArray(hloc,vloc).GT.0) THEN
yTemp = vloc
GO TO 1170
ENDIF
1150 CONTINUE
1160 CONTINUE
1170 IF (yTemp.GT.furthest) furthest=yTemp

vstart=yTemp

DO 1190 vloc=height1,0,-1
DO 1180 hloc=0,width1
IF (imageArray(hloc,vloc).GT.0) THEN
yTemp = vloc
GO TO 1200
ENDIF
1180 CONTINUE
1190 CONTINUE
1200 IF ((height1-yTemp).GT.furthest) furthest=height1-yTemp

vend=yTemp

DO 1220 hloc=0,width1
DO 1210 vloc=0,height1
IF (imageArray(hloc,vloc).GT.0) THEN
xTemp = hloc
GO TO 1230
ENDIF
1210 CONTINUE

```

```

1220 CONTINUE
1230 IF (xTemp.GT.furthest) furthest=xTemp

      hstart=xTemp
880

      DO 1250 hloc=width1,0,-1
      DO 1240 vloc=0,height1
      IF (imageArray(hloc,vloc).GT.0) THEN
        xTemp = hloc
        GO TO 1260
      ENDIF
1240 CONTINUE
1250 CONTINUE
1260 IF ((width1-xTemp).GT.furthest) furthest=width1-xTemp
890

      hend=xTemp

      IF (furthest.LT.bestDistance) THEN
        bestDistance=furthest
        DO 1290 vloc=0,height1
        DO 1280 hloc=0,width1
        bestImage(hloc,vloc)=imageArray(hloc,vloc)
1280 CONTINUE
1290 CONTINUE
900
      ENDIF

      IF (numParticles.GT.bestMass) THEN
        bestMass = numParticles
        DO 1330 vloc=0,height1
        DO 1320 hloc=0,width1
        heavyImage(hloc,vloc)=imageArray(hloc,vloc)
1320 CONTINUE
1330 CONTINUE
910
      ENDIF

      PRINT *, 'Find mass per radius'

      DO 1340 sizeIndex=LARGEST_BOX_INDEX,NUM_BOX_SIZES
        totalMass(sizeIndex) = 0
        lnBoxSizes(sizeIndex) = ALOG(FLOAT(boxSizes(sizeIndex)))
1340 CONTINUE

        configIdx = 0
920
        DO 1390 yr=(yc-minLength/2),(yc+minLength/2)
        DO 1380 xr=(xc-minLength/2),(xc+minLength/2)
        IF (imageArray(xr,yr).GT.0) THEN
          configIdx = configIdx +1
          DO 1370 sizeIndex=LARGEST_BOX_INDEX,NUM_BOX_SIZES
            mass = 0
            yStart = yr - boxSizes(sizeIndex)
            yEnd = yr + boxSizes(sizeIndex)
            xStart = xr - boxSizes(sizeIndex)
            xEnd = xr + boxSizes(sizeIndex)
930
            DO 1360 vloc=yStart,yEnd
            DO 1350 hloc=xStart,xEnd
            temp1=SQRT(FLOAT(vloc-yr)**2+FLOAT(hloc-xr)**2)
            IF (temp1.LE.FLOAT(boxSizes(sizeIndex))) THEN
              IF (imageArray(hloc,vloc).GT.0) mass=mass+1
            ENDIF
1350 CONTINUE
1360 CONTINUE
            totalMass(sizeIndex) = totalMass(sizeIndex) + mass
1370 CONTINUE
940
          ENDIF

1380 CONTINUE
1390 CONTINUE

```



```

DO 1400 sizeIndex=LARGEST_BOX_INDEX,NUM_BOX_SIZES
  lnTotalMass(sizeIndex) =
  C      ALOG(FLOAT(totalMass(sizeIndex))/FLOAT(configIdx))
1400 CONTINUE

PRINT *,'Calculating dimension'

LAST_BOX_INDEX = 24
FIRST_BOX_INDEX = LARGEST_BOX_INDEX
j = LAST_BOX_INDEX - LARGEST_BOX_INDEX + 1
sx = 0.0
sy = 0.0
st2 = 0.0
db = 0.0
DO 1420 i=FIRST_BOX_INDEX,LAST_BOX_INDEX
  sx = sx + lnBoxSizes(i)
  sy = sy + lnTotalMass(i)
1420 CONTINUE
ss = FLOAT(LAST_BOX_INDEX - FIRST_BOX_INDEX) + 1.0
sxcoss = sx/ss

DO 1440 i=FIRST_BOX_INDEX,LAST_BOX_INDEX
  t = lnBoxSizes(i) - sxcoss
  st2 = st2 + t*t
  db = db + t*lnTotalMass(i)
1440 CONTINUE
db = db/st2
sddb = SQRT(1.0/st2)
intcp = (sy - sx*db)/ss
chi2 = 0.0

DO 1460 i=FIRST_BOX_INDEX,LAST_BOX_INDEX
  temp1 = lnTotalMass(i) - intcp - db*lnBoxSizes(i)
  chi2 = chi2 + temp1*temp1
1460 CONTINUE
sigdat = SQRT(chi2/(ss - 2.0))
sddb = sddb*sigdat

dimList(autoCounter)=db
sdDimList(autoCounter)=sddb
timeMassList(autoCounter)=FLOAT(totalTime)/FLOAT(numParticles)
tissueEffList(autoCounter)=FLOAT(numParticles)/FLOAT(tissueParts)
totalEffList(autoCounter)=FLOAT(numParticles)/FLOAT(totalParts)
timeList(autoCounter)=totalTime
massList(autoCounter)=numParticles
tissuePartList(autoCounter)=tissueParts
totalPartList(autoCounter)=totalParts
decayPartList(autoCounter)=numDecayed

PRINT *,'Find minimum path'

DO 1620 vloc=0,height1
  DO 1610 hloc=0,width1
    minPathArray(hloc,vloc)=0
  1610 CONTINUE
1620 CONTINUE

noProgress = .TRUE.
BreakThrough = .FALSE.

stepIndex = 1
DO 1630 hloc=hstart,hend
  IF (imageArray(hloc,vstart).GT.0) THEN
    minPathArray(hloc,vstart)=stepIndex
  ENDF
1630 CONTINUE

```

```

DO 1680 WHILE (.NOT.BreakThrough)
DO 1660 vloc=vstart,vend
DO 1650 hloc=hstart,hend
  IF (minPathArray(hloc,vloc).EQ.stepIndex) THEN

    bTemp1=(imageArray((hloc+1),vloc).GT.0)
    bTemp2=(minPathArray((hloc+1),vloc).EQ.0)
    IF (bTemp1.AND.bTemp2) minPathArray((hloc+1),vloc)=stepIndex+1
    820

    bTemp1=(imageArray((hloc-1),vloc).GT.0)
    bTemp2=(minPathArray((hloc-1),vloc).EQ.0)
    IF (bTemp1.AND.bTemp2) minPathArray((hloc-1),vloc)=stepIndex+1

    bTemp1=(imageArray(hloc,(vloc+1)).GT.0)
    bTemp2=(minPathArray(hloc,(vloc+1)).EQ.0)
    IF (bTemp1.AND.bTemp2) minPathArray(hloc,(vloc+1))=stepIndex+1
    830

    bTemp1=(imageArray(hloc,(vloc-1)).GT.0)
    bTemp2=(minPathArray(hloc,(vloc-1)).EQ.0)
    IF (bTemp1.AND.bTemp2) minPathArray(hloc,(vloc-1))=stepIndex+1

    noProgress = .FALSE.
  ENDIF
1650 CONTINUE
1660 CONTINUE

  IF (noProgress) THEN
    PRINT *, 'No Progress Finding Minimum Path'
    STOP
  ENDIF
  840

  stepIndex=stepIndex+1

  vloc = vend
  hloc = hstart - 1
DO 1670 WHILE (hloc.LT.hend)
  hloc = hloc + 1
  IF (minPathArray(hloc,vloc).NE.0) THEN
    BreakThrough = .TRUE.
    PRINT *, 'Breakthrough minimum path'
    breakPoint = hloc
    hloc = hend
  ENDIF
1670 END DO
  850

1680 END DO
  860

  LARGEST_BOX_INDEX = 1
DO WHILE (boxSizes(LARGEST_BOX_INDEX).GE.((vend-vstart)/4))
  LARGEST_BOX_INDEX = LARGEST_BOX_INDEX + 1
END DO

  vloc = vend
  hloc = breakPoint
  pointIndex = 0
  stepIndex = minPathArray(hloc,vloc) - 1
  minPathArray(hloc,vloc) = -1
  minPath(pointIndex,0) = hloc
  minPath(pointIndex,1) = vloc
  870

DO 1720 WHILE (vloc.GT.vstart)
  xs = hloc - 1
  ys = vloc - 1
  xe = hloc + 1
  ye = vloc + 1
DO 1710 y=ys, ye
  DO 1700 x=xs, xe
    880

```

```

      IF (minPathArray(x,y).EQ.stepIndex) THEN
        minPathArray(x,y) = -1
        stepIndex = stepIndex - 1
        pointIndex = pointIndex + 1
        hloc = x
        vloc = y
        minPath(pointIndex,0) = hloc
        minPath(pointIndex,1) = vloc
        GO TO 1720
      ENDIF
1700 CONTINUE
1710 CONTINUE
1720 END DO

      DO 1780 sizeIndex=LARGEST_BOX_INDEX,NUM_BOX_SIZES
        eSize = FLOAT(boxSizes(sizeIndex))
        occBox = 0
        pointLoc = 0
        DO 1760 i=0,pointIndex
          dx = minPath(i,0) - minPath(pointLoc,0)
          dy = minPath(i,1) - minPath(pointLoc,1)
          r1 = SQRT(FLOAT(dx*dx) + FLOAT(dy*dy))
          IF (r1.GE.eSize) THEN
            pointLoc = i
            occBox = occBox + 1
          ENDIF
1760 CONTINUE

          IF (pointLoc.LT.pointIndex) occBox=occBox+1

          totalMass(sizeIndex) = occBox
          lnBoxSizes(sizeIndex) = ALOG(FLOAT(boxSizes(sizeIndex)))
          lnTotalMass(sizeIndex) = ALOG(FLOAT(totalMass(sizeIndex)))
1780 CONTINUE

          PRINT *, 'Calculating minimum-path dimension'

          LAST_BOX_INDEX = 24
          FIRST_BOX_INDEX = LARGEST_BOX_INDEX
          j = LAST_BOX_INDEX - LARGEST_BOX_INDEX + 1
          sx = 0.0
          sy = 0.0
          st2 = 0.0
          db = 0.0
          DO 1820 i=FIRST_BOX_INDEX, LAST_BOX_INDEX
            sx = sx + lnBoxSizes(i)
            sy = sy + lnTotalMass(i)
1820 CONTINUE
            ss = FLOAT(LAST_BOX_INDEX - FIRST_BOX_INDEX) + 1.0
            sxoss = sx/ss

            DO 1840 i=FIRST_BOX_INDEX, LAST_BOX_INDEX
              t = lnBoxSizes(i) - sxoss
              st2 = st2 + t*t
              db = db + t*lnTotalMass(i)
1840 CONTINUE
              db = db/st2
              sddb = SQRT(1.0/st2)
              intcp = (sy - sx*db)/ss
              chi2 = 0.0

              DO 1860 i=FIRST_BOX_INDEX, LAST_BOX_INDEX
                temp1 = lnTotalMass(i) - intcp - db*lnBoxSizes(i)
                chi2 = chi2 + temp1*temp1
1860 CONTINUE
              sigdat = SQRT(chi2/(ss - 2.0))
              sddb = sddb*sigdat

```

```

mpdimList(autoCounter)=0.0-db
sdMpdimList(autoCounter)=sddb                                     950

i=autoCounter
WRITE (16,2250) i,dimList(i),sdDimList(i),
C      mpdimList(i),sdMpdimList(i),timeMassList(i),
C      tissueEffList(i),totalEffList(i),timeList(i),
C      massList(i),tissuePartList(i),
C      totalPartList(i),decayPartList(i)

PRINT '(1X,A,I5,A,I5)', 'Finished Iteration ',autoCounter,
C      ' out of ',AUTO_ITERATIONS                                     960

IF (autoCounter.LT.AUTO_ITERATIONS) GO TO 10

CLOSE (UNIT=16)

denominator = 0.0
numerator = 0.0
DO 1880 i=1,AUTO_ITERATIONS
denominator=denominator+1.0/sdMpdimList(i)**2
numerator=numerator+mpdimList(i)*(1.0/sdMpdimList(i)**2)
1880 CONTINUE
mpdim=numerator/denominator

numerator = 0.0
DO 1890 i=1,AUTO_ITERATIONS
numerator=numerator+(mpdimList(i)-mpdim)**2
1890 CONTINUE
sdmpdim=SQRT(numerator/FLOAT(AUTO_ITERATIONS-1))

denominator = 0.0
numerator = 0.0
DO 1900 i=1,AUTO_ITERATIONS
denominator=denominator+1.0/sdDimList(i)**2
numerator=numerator+dimList(i)*(1.0/sdDimList(i)**2)
1900 CONTINUE
db=numerator/denominator

numerator = 0.0
DO 1910 i=1,AUTO_ITERATIONS
numerator=numerator+(dimList(i)-db)**2
1910 CONTINUE
sddb=SQRT(numerator/FLOAT(AUTO_ITERATIONS-1))

numerator = 0.0
DO 1920 i=1,AUTO_ITERATIONS
numerator=numerator+timeMassList(i)
1920 CONTINUE
timeMassAvg=numerator/FLOAT(AUTO_ITERATIONS)

numerator = 0.0
DO 1930 i=1,AUTO_ITERATIONS
numerator=numerator+(timeMassList(i)-timeMassAvg)**2
1930 CONTINUE
timeMassSD=SQRT(numerator/FLOAT(AUTO_ITERATIONS-1))

numerator = 0.0
DO 1940 i=1,AUTO_ITERATIONS
numerator=numerator+tissueEffList(i)
1940 CONTINUE
tissueEffAvg=numerator/FLOAT(AUTO_ITERATIONS)                                     1010

numerator = 0.0
DO 1950 i=1,AUTO_ITERATIONS
numerator=numerator+(tissueEffList(i)-tissueEffAvg)**2
1950 CONTINUE
tissueEffSD=SQRT(numerator/FLOAT(AUTO_ITERATIONS-1))

```

```

numerator = 0.0
DO 1960 i=1,AUTO_ITERATIONS
numerator=numerator+totalEffList(i)
1960 CONTINUE
totalEffAvg=numerator/FLOAT(AUTO_ITERATIONS)

numerator = 0.0
DO 1970 i=1,AUTO_ITERATIONS
numerator=numerator+(totalEffList(i)-totalEffAvg)**2
1970 CONTINUE
totalEffSD=SQRT(numerator/FLOAT(AUTO_ITERATIONS-1))

numerator = 0.0
DO 1980 i=1,AUTO_ITERATIONS
numerator=numerator+FLOAT(timeList(i))
1980 CONTINUE
timeAvg=numerator/FLOAT(AUTO_ITERATIONS)

numerator = 0.0
DO 1990 i=1,AUTO_ITERATIONS
numerator=numerator+(FLOAT(timeList(i))-timeAvg)**2
1990 CONTINUE
timeSD=SQRT(numerator/FLOAT(AUTO_ITERATIONS-1))

numerator = 0.0
DO 2000 i=1,AUTO_ITERATIONS
numerator=numerator+FLOAT(massList(i))
2000 CONTINUE
massAvg=numerator/FLOAT(AUTO_ITERATIONS)

numerator = 0.0
DO 2010 i=1,AUTO_ITERATIONS
numerator=numerator+(FLOAT(massList(i))-massAvg)**2
2010 CONTINUE
massSD=SQRT(numerator/FLOAT(AUTO_ITERATIONS-1))

numerator = 0.0
DO 2020 i=1,AUTO_ITERATIONS
numerator=numerator+FLOAT(tissuePartList(i))
2020 CONTINUE
tissuePartAvg=numerator/FLOAT(AUTO_ITERATIONS)

numerator = 0.0
DO 2030 i=1,AUTO_ITERATIONS
numerator=numerator+(FLOAT(tissuePartList(i))-tissuePartAvg)**2
2030 CONTINUE
tissuePartSD=SQRT(numerator/FLOAT(AUTO_ITERATIONS-1))

numerator = 0.0
DO 2040 i=1,AUTO_ITERATIONS
numerator=numerator+FLOAT(totalPartList(i))
2040 CONTINUE
totalPartAvg=numerator/FLOAT(AUTO_ITERATIONS)

numerator = 0.0
DO 2050 i=1,AUTO_ITERATIONS
numerator=numerator+(FLOAT(totalPartList(i))-totalPartAvg)**2
2050 CONTINUE
totalPartSD=SQRT(numerator/FLOAT(AUTO_ITERATIONS-1))

numerator = 0.0
DO 2060 i=1,AUTO_ITERATIONS
numerator=numerator+FLOAT(decayPartList(i))
2060 CONTINUE
decayPartAvg=numerator/FLOAT(AUTO_ITERATIONS)

numerator = 0.0

```

```

DO 2070 i=1,AUTO_ITERATIONS
  numerator=numerator+(FLOAT(decayPartList(i))-decayPartAvg)**2
2070 CONTINUE
  decayPartSD=SQRT(numerator/FLOAT(AUTO_ITERATIONS-1))

  CALL ITIME(tArray)
  compTime=tArray(3)+tArray(2)*60+tArray(1)*3600-compTime
  PRINT '(1X,A,I10)', 'Execution Time (secs): ', compTime

  OPEN (UNIT=19,FILE='Model.Averages',STATUS='NEW')
  WRITE (19,2200) ' '
  WRITE (19,2200) 'Averages:'
  WRITE (19,2240) 'Fractal Dimension:',db,' +/-',sddb
  WRITE (19,2240) 'Minimum-Path Dimension:',mpdim,' +/-',sdmpdim
  WRITE (19,2240) 'Time/Mass:',timeMassAvg,' +/-',timeMassSD
  WRITE (19,2240) 'Tis. Efficn.:',tissueEffAvg,' +/-',tissueEffSD
  WRITE (19,2240) 'Tot. Efficn.:',totalEffAvg,' +/-',totalEffSD
  WRITE (19,2240) 'Time:',timeAvg,' +/-',timeSD
  WRITE (19,2240) 'Mass:',massAvg,' +/-',massSD
  WRITE (19,2240) 'Tis. Prtcls:',tissuePartAvg,' +/-',tissuePartSD
  WRITE (19,2240) 'Tot. Prtcls:',totalPartAvg,' +/-',totalPartSD
  WRITE (19,2240) 'Dec. Prtcls:',decayPartAvg,' +/-',decayPartSD
  CLOSE (UNIT=19)

  OPEN (UNIT=17,FILE='Model.Best',STATUS='NEW')
  DO 2120 vloc=0,height1
  DO 2110 hloc=0,width2
    WRITE (17,2260) bestImage(hloc,vloc),'T'
2110 CONTINUE
    WRITE (17,2260) bestImage(width1,vloc),'C'
2120 CONTINUE
  CLOSE (UNIT=17)

  OPEN (UNIT=18,FILE='Model.Heavy',STATUS='NEW')
  DO 2140 vloc=0,height1
  DO 2130 hloc=0,width2
    WRITE (18,2260) heavyImage(hloc,vloc),'T'
2130 CONTINUE
    WRITE (18,2260) heavyImage(width1,vloc),'C'
2140 CONTINUE
  CLOSE (UNIT=18)

2200 FORMAT (1X,A)
2210 FORMAT (1X,A,I9)
2220 FORMAT (1X,A,F9.7,1X,A)
2230 FORMAT (1X,A,F9.5)
2240 FORMAT (1X,A,F16.7,A,F16.7)
2250 FORMAT (1X,I3,1X,F6.4,1X,F6.4,1X,F6.4,1X,F6.4,
  C      F8.5,F8.5,F8.5,I7,I6,I7,I7,I6)
2260 FORMAT (1X,I4,A)
2270 FORMAT (1X,A,A)

  END

```

A.7 3-D Growth Modeling Program

```

PROGRAM DoModelTime

REAL*4 RNUNF

*   Assign parameters:
INTEGER*4 AUTO_ITERATIONS,MAX_LENGTH,MAX_LENGTH1
PARAMETER (AUTO_ITERATIONS=10,MAX_LENGTH=32,MAX_LENGTH1=31)
INTEGER*4 MAX_TIME,MAX_NUM_PARTICLES
PARAMETER (MAX_TIME=1000000,MAX_NUM_PARTICLES=50000)
INTEGER*4 NO_PROD_RADIUS                                10
PARAMETER (NO_PROD_RADIUS=5)
INTEGER*4 NUM_BOX_SIZES
PARAMETER (NUM_BOX_SIZES=25)
INTEGER*4 MAX_PATH_LENGTH
PARAMETER (MAX_PATH_LENGTH=1000)

*   Declare image-size variables:
INTEGER*4 width,width1,width2,height,height1,height2
INTEGER*4 depth,depth1,depth2
REAL*4 imageVolume                                    20

*   Declare multi-purpose variables:
INTEGER*4 vloc,hloc,xTemp,yTemp,xNo,yNo,yT,xT
INTEGER*4 zloc,zTemp,zNo,zT
INTEGER*4 k,i,j
INTEGER*4 longtmp(0:5)
LOGICAL*4 bTemp1,bTemp2
REAL*4 numerator,denominator
INTEGER*4 compTime,tArray(1:3)                                    30

*   Declare model parameters:
INTEGER*4 halfLife,growthWaitUnits,intL
INTEGER*4 numGroups,growthThreshold,releaseThreshold
LOGICAL*4 homogeneousSub,homogeneousDif,centerSeed
REAL*4 productionRate,stickingProb,extraRelease,growthRange
REAL*4 releaseAtGrowthSite,tau,finTL
LOGICAL*4 waitUnit,uniformParticleDist

*   Declare model variables:
INTEGER*4 xCntr,yCntr,release,numRelease,autoCounter          40
INTEGER*4 zCntr
INTEGER*4 timeUnits,hitUnits,numDecayed,numParticles,occNeighbors
INTEGER*4 totalTime,highestParticle,numNew,emptyParticle
INTEGER*4 totalParts,tissueParts,extraParticles,growthSites
REAL*4 decayProb,weakest,frac
LOGICAL*4 BreakThrough,keepWaiting,foundEmpty
INTEGER*4 furthest,bestDistance,bestMass

*   Declare final image variables:
INTEGER*4 pGroupSize,pAge                                    50

*   Declare arrays:
INTEGER*4 imageArray(0:MAX_LENGTH1,0:MAX_LENGTH1,0:MAX_LENGTH1)
REAL*4 strengthArrayDif(0:MAX_LENGTH1,0:MAX_LENGTH1,0:MAX_LENGTH1)
REAL*4 strengthArraySub(0:MAX_LENGTH1,0:MAX_LENGTH1,0:MAX_LENGTH1)
INTEGER*4 hitArray(0:MAX_LENGTH1,0:MAX_LENGTH1,0:MAX_LENGTH1)
INTEGER*4 xParticle(1:MAX_NUM_PARTICLES)
INTEGER*4 yParticle(1:MAX_NUM_PARTICLES)
INTEGER*4 zParticle(1:MAX_NUM_PARTICLES)
INTEGER*4 ageParticle(1:MAX_NUM_PARTICLES)
LOGICAL*4 activeParticle(1:MAX_NUM_PARTICLES)                    60

*   Declare result variables:
INTEGER*4 bestImage(0:MAX_LENGTH1,0:MAX_LENGTH1,0:MAX_LENGTH1)

```

```

INTEGER*4 heavyImage(0:MAX_LENGTH1,0:MAX_LENGTH1,0:MAX_LENGTH1)
REAL*4 dimList(0:AUTO_ITERATIONS)
REAL*4 sdDimList(0:AUTO_ITERATIONS)
REAL*4 mpdimList(0:AUTO_ITERATIONS)
REAL*4 sdMpdimList(0:AUTO_ITERATIONS)
REAL*4 timeMassList(0:AUTO_ITERATIONS)
REAL*4 tissueEffList(0:AUTO_ITERATIONS)
REAL*4 totalEffList(0:AUTO_ITERATIONS)
INTEGER*4 timeList(0:AUTO_ITERATIONS),massList(0:AUTO_ITERATIONS)
INTEGER*4 tissuePartList(0:AUTO_ITERATIONS)
INTEGER*4 totalPartList(0:AUTO_ITERATIONS)
INTEGER*4 decayPartList(0:AUTO_ITERATIONS)
REAL*4 timeMassAvg,totalEffAvg,tissueEffAvg,timeAvg,massAvg
REAL*4 tissuePartAvg,totalPartAvg,decayPartAvg
REAL*4 timeMassSD,totalEffSD,tissueEffSD,timeSD,massSD
REAL*4 tissuePartSD,totalPartSD,decayPartSD
REAL*4 mpdim,sdmpdim
70

*   Declare mass-radius variables:
INTEGER*4 sizeIndex,xStart,yStart,xEnd,yEnd,mass,xc,yc
INTEGER*4 zStart,zEnd,zc
INTEGER*4 xr,yr,minLength
INTEGER*4 zr
INTEGER*4 LARGEST_BOX_INDEX,FIRST_BOX_INDEX,LAST_BOX_INDEX
REAL*4 temp1,temp2
REAL*4 sx,sy,st2,db,ss,sxoss,t,sddb,chi2,sigdat,intcp
INTEGER*4 boxSizes(1:NUM_BOX_SIZES),totalMass(1:NUM_BOX_SIZES)
REAL*4 lnBoxSizes(1:NUM_BOX_SIZES),lnTotalMass(1:NUM_BOX_SIZES)
90

*   Declare minimum path variables:
LOGICAL*4 noProgress
INTEGER*4 minPathArray(0:MAX_LENGTH1,0:MAX_LENGTH1,0:MAX_LENGTH1)
INTEGER*4 stepIndex,vstart,vend,hstart,hend
INTEGER*4 dstart,dend
INTEGER*4 breakPoint,x,y,xs,ys,xe,ye,xs,ys
INTEGER*4 zbreakPoint,z,ze,zs
INTEGER*4 minPath(0:MAX_PATH_LENGTH,0:2)
INTEGER*4 pointIndex,pointLoc,occBox,configIdx
INTEGER*4 dx,dy
INTEGER*4 dz
REAL*4 eSize,r1

CALL ITIME(tArray)
compTime=tArray(3)+tArray(2)*60+tArray(1)*3600

*   Initialize parameters:
intL=32768
fintL=32768.0
110

*   Initialize size variables:
width = MAX_LENGTH
width1 = width - 1
width2 = width - 2
height = MAX_LENGTH
height1 = height - 1
height2 = height - 2
depth = MAX_LENGTH
depth1 = depth - 1
depth2 = depth - 2
120

*   Initialize dimension measurement parameters:
boxSizes(1) = 512
temp1 = 512.0
DO 5 k=2,NUM_BOX_SIZES
4  temp2 = 0.793700526*temp1
   j = NINT(temp2)
   temp1 = temp2
   IF (j.EQ.boxSizes(k-1)) GO TO 4
130

```


boxSizes(k) = j
5 CONTINUE

```
* Assign Parameters:
homogeneousSub = .FALSE.
homogeneousDif = .TRUE.
centerSeed = .TRUE.
waitUnit = .TRUE.
growthWaitUnits = 10
halfLife = 1000000
tau = FLOAT(halfLife)/ALOG(2.0)
numGroups = 250
uniformParticleDist = .FALSE.
imageVolume = FLOAT(height)*FLOAT(width)*FLOAT(depth)
productionRate = 0.000056234133
stickingProb = 1.0
extraRelease = 0.0
releaseAtGrowthSite = 3.0
growthThreshold = 1
releaseThreshold = 1
growthRange = 0.5

OPEN (UNIT=15,FILE='Model.Specs',STATUS='NEW')
WRITE (15,2200) 'Model Specifications:'
IF (homogeneousSub) THEN
  WRITE (15,2200) 'Homogeneous Substrate'
ELSE
  WRITE (15,2200) 'Inhomogeneous Substrate'
ENDIF
IF (homogeneousDif) THEN
  WRITE (15,2200) 'Homogeneous Diffusion'
ELSE
  WRITE (15,2200) 'Inhomogeneous Diffusion'
ENDIF
IF (centerSeed) THEN
  WRITE (15,2200) 'Center Seed'
ELSE
  WRITE (15,2200) 'Multiple Seeds'
ENDIF
IF (waitUnit) THEN
  WRITE (15,2200) 'Wait Unit: TIME'
ELSE
  WRITE (15,2200) 'Wait Unit: HIT'
ENDIF
WRITE (15,2210) 'Growth Wait Units :',growthWaitUnits
WRITE (15,2210) 'Particle Half-life:',halfLife
IF (uniformParticleDist) THEN
  WRITE (15,2200) 'Uniform particle origin'
ELSE
  WRITE (15,2200) 'Particle origin beyond network'
ENDIF
WRITE (15,2220) 'Production Rate: ',productionRate,
C 'particles/pixel*time'
WRITE (15,2230) 'Interaction Probability:',stickingProb
WRITE (15,2230) 'Extra release per hit:',extraRelease
WRITE (15,2230) 'Extra release at growth site:',
C releaseAtGrowthSite
WRITE (15,2210) 'Growth threshold:',growthThreshold
WRITE (15,2210) 'Extra release threshold:',releaseThreshold
WRITE (15,2230) 'Growth Range: 0.0 -',growthRange
CLOSE (UNIT=15)

OPEN (UNIT=16,FILE='Model.Data',STATUS='NEW')
WRITE (16,2270)
C ' No Dm-r Dmp T/M tis-E',
C ' tot-E Time Mass Tis Tot Dec'
```

```

bestDistance = MAX_LENGTH/2
bestMass = 0

* Seeding code:
CALL RNOPT(6)
CALL RNSET(0)
* End of seeding code

* Initialize iteration counter:
autoCounter = 0
10 autoCounter = autoCounter + 1

* Assign growth substrate strengths:
IF (.NOT.homogeneousSub) THEN
  PRINT *, 'Generating random substrate strengths...'
  DO 110 vloc=0,height1
    DO 105 hloc=0,width1
      DO 100 zloc=0,depth1
        strengthArraySub(hloc,vloc,zloc)= RNUNF()
100 CONTINUE
105 CONTINUE
110 CONTINUE
  PRINT *, 'Random growth substrate generated.'
ELSE
  DO 130 vloc=0,height1
    DO 125 hloc=0,width1
      DO 120 zloc=0,depth1
        strengthArraySub(hloc,vloc,zloc)=0.5
120 CONTINUE
125 CONTINUE
130 CONTINUE
ENDIF

* Assign diffusion substrate strengths:
IF (.NOT.homogeneousDif) THEN
  PRINT *, 'Generating random diffusion strengths...'
  DO 160 vloc=0,height1
    DO 155 hloc=0,width1
      DO 150 zloc=0,depth1
        strengthArrayDif(hloc,vloc,zloc)= RNUNF()
150 CONTINUE
155 CONTINUE
160 CONTINUE
  PRINT *, 'Random diffusion substrate generated.'
ENDIF

* Initialize model variables:

DO 200 i=1,MAX_NUM_PARTICLES
  activeParticle(i)=.FALSE.
200 CONTINUE

BreakThrough = .FALSE.
numDecayed = 0
totalTime = 0
totalParts = 0
tissueParts = 0
extraParticles = 0

DO 220 vloc=0,height1
  DO 215 hloc=0,width1
    DO 210 zloc=0,depth1
      imageArray(hloc,vloc,zloc)=0
210 CONTINUE

```

```

215 CONTINUE
220 CONTINUE
270

IF (centerSeed) THEN
  yCntr = height/2
  xCntr = width/2
  zCntr = depth/2
  numParticles = 1
  imageArray(xCntr,yCntr,zCntr)=numParticles

IF (.NOT.uniformParticleDist) THEN
  DO 260 zNo=-NO_PROD_RADIUS,NO_PROD_RADIUS
    zT = zNo + zCntr
    IF (zT.GT.depth1) zT=zT-depth
    IF (zT.LT.0) zT=depth-zT
    DO 250 yNo=-NO_PROD_RADIUS,NO_PROD_RADIUS
      yT = yNo + yCntr
      IF (yT.GT.height1) yT=yT-height
      IF (yT.LT.0) yT=height-yT
      DO 240 xNo=-NO_PROD_RADIUS,NO_PROD_RADIUS
        xT = xNo + xCntr
        IF (xT.GT.width1) xT=xT-width
        IF (xT.LT.0) xT=width-xT
        k=xNo*xNo + yNo*yNo* + zNo*zNo
        IF (SQRT(FLOAT(k)).LT.NO_PROD_RADIUS) THEN
          IF (imageArray(xT,yT,zT).EQ.0) imageArray(xT,yT,zT)=-1
        ENDIF
240 CONTINUE
250 CONTINUE
260 CONTINUE
      ENDIF
    ELSE
      PRINT *,'Only center-seed option is available!'
      STOP
    ENDIF
300

* ##### Main loop until BreakThrough #####
DO 1000 WHILE (.NOT.BreakThrough)
  keepWaiting=.TRUE.
  timeUnits=0
  hitUnits=0
310

  DO 310 vloc=0,height1
    DO 305 hloc=0,width1
      DO 300 zloc=0,depth1
        hitArray(hloc,vloc,zloc)=0
300 CONTINUE
305 CONTINUE
310 CONTINUE

    highestParticle=0
    DO 320 i=1,MAX_NUM_PARTICLES
      IF (activeParticle(i)) highestParticle=i
320 CONTINUE

* Loop waiting for time for growth:
DO 700 WHILE (keepWaiting)

  timeUnits=timeUnits+1
  totalTime=totalTime+1
330

* Advance existing particles:
DO 400 i=1,highestParticle
  IF (activeParticle(i)) THEN

    ageParticle(i)=ageParticle(i)+1

```

```

*      Takes into account only the case where homogeneousDif=TRUE:
      k=AINT(6.0*RNUNF()+1
      GO TO (330,340,350,360,370,380), k
330    zTemp = zParticle(i) + 1
      yTemp = yParticle(i)
      xTemp = xParticle(i)
      IF (zTemp.EQ.depth) zTemp=0
      GO TO 390
340    zTemp = zParticle(i) - 1
      yTemp = yParticle(i)
      xTemp = xParticle(i)
      IF (zTemp.EQ.-1) zTemp=depth1
      GO TO 390
350    xTemp = xParticle(i) + 1
      yTemp = yParticle(i)
      zTemp = zParticle(i)
      IF (xTemp.EQ.width) xTemp=0
      GO TO 390
360    xTemp = xParticle(i) - 1
      yTemp = yParticle(i)
      zTemp = zParticle(i)
      IF (xTemp.EQ.-1) xTemp=width1
      GO TO 390
370    yTemp = yParticle(i) - 1
      xTemp = xParticle(i)
      zTemp = zParticle(i)
      IF (yTemp.EQ.-1) yTemp=height1
      GO TO 390
380    yTemp = yParticle(i) + 1
      xTemp = xParticle(i)
      zTemp = zParticle(i)
      IF (yTemp.EQ.height) yTemp=0
390    IF (imageArray(xTemp,yTemp,zTemp).LE.0) THEN
      xParticle(i)=xTemp
      yParticle(i)=yTemp
      zParticle(i)=zTemp
      ENDIF
400  CONTINUE

*      Produce new particles:

      numNew=AINT(productionRate*imageVolume)
      frac=productionRate*imageVolume-1.0*FLOAT(numNew)
      IF (RNUNF()).LT.frac) numNew=numNew+1
      emptyParticle = 1
      DO 460 i=1,numNew
      xTemp = NINT(RNUNF()*width1)
      yTemp = NINT(RNUNF()*height1)
      zTemp = NINT(RNUNF()*depth1)
      IF (imageArray(xTemp,yTemp,zTemp).EQ.0) THEN
      foundEmpty = .FALSE.
      k = emptyParticle - 1
      DO 450 WHILE (k.LT.MAX_NUM_PARTICLES)
      k = k + 1
      IF (.NOT.activeParticle(k)) THEN
      emptyParticle = k
      foundEmpty = .TRUE.
      k = MAX_NUM_PARTICLES
      ENDIF
450  END DO

      IF (.NOT.foundEmpty) THEN
      PRINT *,'Too Many Particles!'
      STOP
      ENDIF

      tissueParts = tissueParts + 1

```

```

totalParts = totalParts + 1
activeParticle(emptyParticle)=.TRUE.
xParticle(emptyParticle)=xTemp
yParticle(emptyParticle)=yTemp
zParticle(emptyParticle)=zTemp
ageParticle(emptyParticle)=1
IF (emptyParticle.GT.highestParticle)
C     highestParticle=emptyParticle
ENDIF
460 CONTINUE

*   Degrade old particles:

DO 500 i=1,highestParticle
IF (activeParticle(i)) THEN
decayProb = EXP(-FLOAT(ageParticle(i))/tau)/tau
IF (RNUNF()).LT.decayProb) THEN
    numDecayed = numDecayed + 1
    activeParticle(i)=.FALSE.
ENDIF
ENDIF
500 CONTINUE

*   Mark hits:
DO 600 i=1,highestParticle
IF (activeParticle(i)) THEN
xTemp = xParticle(i)
yTemp = yParticle(i)
zTemp = zParticle(i)
bTemp1 = ((xTemp.LT.width1).AND.(yTemp.LT.height1))
bTemp1 = (bTemp1.AND.(zTemp.LT.depth1))
bTemp2 = ((xTemp.GT.0).AND.(yTemp.GT.0))
bTemp2 = (bTemp2.AND.(zTemp.GT.0))
IF (bTemp1.AND.bTemp2) THEN
longtmp(0)=
C     AINT(FLOAT(intL-1+imageArray((xTemp+1),yTemp,zTemp)))/
C     fintL)
longtmp(1)=
C     AINT(FLOAT(intL-1+imageArray((xTemp-1),yTemp,zTemp)))/
C     fintL)
longtmp(2)=
C     AINT(FLOAT(intL-1+imageArray(xTemp,(yTemp+1),zTemp)))/
C     fintL)
longtmp(3)=
C     AINT(FLOAT(intL-1+imageArray(xTemp,(yTemp-1),zTemp)))/
C     fintL)
longtmp(4)=
C     AINT(FLOAT(intL-1+imageArray(xTemp,yTemp,(zTemp+1)))/
C     fintL)
longtmp(5)=
C     AINT(FLOAT(intL-1+imageArray(xTemp,yTemp,(zTemp-1)))/
C     fintL)
occNeighbors=longtmp(0)+longtmp(1)+longtmp(2)+longtmp(3)+
C     longtmp(4)+longtmp(5)
IF (occNeighbors.GT.0) THEN
IF (RNUNF()).LT.(stickingProb*FLOAT(occNeighbors))) THEN
activeParticle(i)=.FALSE.
hitArray(xTemp,yTemp,zTemp)=hitArray(xTemp,yTemp,zTemp)+1
hitUnits = hitUnits + 1
IF (MOD(hitArray(xTemp,yTemp,zTemp),releaseThreshold).EQ.0)
C     THEN
emptyParticle = 1
numRelease = AINT(extraRelease)
frac = extraRelease - FLOAT(numRelease)
IF (RNUNF()).LT.frac) numRelease=numRelease+1
DO 580 release=1,numRelease
foundEmpty=.FALSE.

```

```

k=emptyParticle - 1
DO 540 WHILE (k.LT.i)
  k = k + 1
  IF (.NOT.activeParticle(k)) THEN
    emptyParticle = k
    foundEmpty = .TRUE.
    k = i
  ENDIF
540  END DO
  IF (.NOT.foundEmpty) THEN
    k=highestParticle
    DO 560 WHILE (k.LT.MAX_NUM_PARTICLES)
      k = k + 1
      IF (.NOT.activeParticle(k)) THEN
        emptyParticle = k
        foundEmpty = .TRUE.
        k = MAX_NUM_PARTICLES
      ENDIF
560  END DO
    ENDIF
    IF (.NOT.foundEmpty) THEN
      PRINT *, 'Too Many Particles!'
      STOP
    ENDIF
    extraParticles = extraParticles + 1
    totalParts = totalParts + 1
    activeParticle(emptyParticle) = .TRUE.
    xParticle(emptyParticle) = xTemp
    yParticle(emptyParticle) = yTemp
    zParticle(emptyParticle) = zTemp
    ageParticle(emptyParticle) = 1
580  CONTINUE
  ENDIF
  ENDIF
  ENDIF
  ENDIF
600 CONTINUE
810

*   Check if time for growth:
  IF (waitUnit) THEN
    IF (timeUnits.EQ.growthWaitUnits) keepWaiting=.FALSE.
  ELSE
    IF (hitUnits.GE.growthWaitUnits) keepWaiting=.FALSE.
  ENDIF

  IF (totalTime.EQ.MAX_TIME) THEN
    PRINT *, 'Time exceeded maximum'
    STOP
  ENDIF

700 END DO
*   End of loop waiting for growth event time

*   Begin growth:
  IF (hitUnits.GT.0) THEN
    growthSites = 0
    weakest = 1.0
    DO 720 vloc=0,height1
      DO 715 hloc=0,width1
        DO 710 zloc=0,depth1
          IF (hitArray(hloc,vloc,zloc).GE.growthThreshold) THEN
            IF (strengthArraySub(hloc,vloc,zloc).LT.weakest) THEN
              weakest=strengthArraySub(hloc,vloc,zloc)
            ENDIF
          ENDIF
        DO 710 CONTINUE
      DO 715 CONTINUE
    DO 720 CONTINUE
  ENDIF
710 CONTINUE
810

```

```

715 CONTINUE
720 CONTINUE

DO 900 vloc=0,height1
DO 890 hloc=0,width1
DO 880 zloc=0,depth1
IF (hitArray(hloc,vloc,zloc).GE.growthThreshold) THEN
  bTemp1=(strengthArraySub(hloc,vloc,zloc).LE.growthRange)
  bTemp2=(strengthArraySub(hloc,vloc,zloc).EQ.weakest)
  IF (bTemp1.OR.bTemp2) THEN
    xTemp = hloc
    yTemp = vloc
    zTemp = zloc
    growthSites = growthSites + 1
    numParticles = numParticles + 1
    imageArray(xTemp,yTemp,zTemp) = numParticles
    bTemp1=((xTemp.EQ.width2).OR.(xTemp.EQ.1))
    bTemp1=(bTemp1.OR.((zTemp.EQ.depth2).OR.(zTemp.EQ.1)))
    bTemp2=((yTemp.EQ.height2).OR.(yTemp.EQ.1))
    IF (bTemp1.OR.bTemp2) BreakThrough=.TRUE.
  
```

550

```

*
  Mark no production area:
  IF (.NOT.uniformParticleDist) THEN
    DO 760 zNo=-NO_PROD_RADIUS,NO_PROD_RADIUS
      zT = zNo + zTemp
      IF (zT.GT.depth1) zT=zT-depth
      IF (zT.LT.0) zT=depth-zT
      DO 755 yNo=-NO_PROD_RADIUS,NO_PROD_RADIUS
        yT = yNo + yTemp
        IF (yT.GT.height1) yT=yT-height
        IF (yT.LT.0) yT=height-yT
        DO 750 xNo=-NO_PROD_RADIUS,NO_PROD_RADIUS
          xT = xNo + xTemp
          IF (xT.GT.width1) xT=xT-width
          IF (xT.LT.0) xT=width-xT
          k=xNo*xNo + yNo*yNo + zNo*zNo
          IF (SQRT(FLOAT(k)).LE.NO_PROD_RADIUS) THEN
            IF (imageArray(xT,yT,zT).EQ.0) imageArray(xT,yT,zT)=-1
            ENDIF
          
```

570

```

750 CONTINUE
755 CONTINUE
760 CONTINUE
ENDIF
*
  End marking no production area

*
  Remove additional particles currently residing on growth site:
  DO 770 i=1,highestParticle
    IF (activeParticle(i)) THEN
      bTemp1 = (xParticle(i).EQ.xTemp)
      bTemp2 = (yParticle(i).EQ.yTemp)
      bTemp2 = (bTemp2.AND.(zParticle(i).EQ.zTemp))
      IF (bTemp1.AND.bTemp2)
        C
          activeParticle(i)=.FALSE.
        ENDIF
      
```

590

```

770 CONTINUE
*
  End removal

*
  Release additional particles to nearest neighbors of growth site:
  DO 780 i=0,5
    longtmp(i)=0
    CONTINUE
    IF (imageArray((xTemp+1),yTemp,zTemp).LE.0) longtmp(0)=1
    IF (imageArray((xTemp-1),yTemp,zTemp).LE.0) longtmp(1)=1
    IF (imageArray(xTemp,(yTemp+1),zTemp).LE.0) longtmp(2)=1
    IF (imageArray(xTemp,(yTemp-1),zTemp).LE.0) longtmp(3)=1
    IF (imageArray(xTemp,yTemp,(zTemp+1)).LE.0) longtmp(4)=1
    IF (imageArray(xTemp,yTemp,(zTemp-1)).LE.0) longtmp(5)=1
  
```

600

```

numRelease = AINT(releaseAtGrowthSite)
frac = releaseAtGrowthSite - FLOAT(numRelease)
IF (RNUNF().LT.frac) numRelease=numRelease+1
bTemp1=((longtmp(0)+longtmp(1)+longtmp(2)+longtmp(3)+
longtmp(4)+longtmp(5)).EQ.0)
C IF (bTemp1) numRelease=0
release = 0
DO 870 WHILE (release.LT.numRelease)
* Takes into account only the case where homogeneousDif=TRUE
release = release + 1
k = AINT(6.0*RNUNF())
IF (k.EQ.6) k=5
IF (longtmp(k).NE.1) THEN
release=release-1
ELSE
foundEmpty = .FALSE.
i = 0
DO 810 WHILE (i.LT.MAX_NUM_PARTICLES)
i = i + 1
IF (.NOT.activeParticle(i)) THEN
emptyParticle = i
foundEmpty = .TRUE.
i = MAX_NUM_PARTICLES
ENDIF
810 END DO
IF (foundEmpty) THEN
extraParticles = extraParticles + 1
totalParts = totalParts + 1
activeParticle(emptyParticle) = .TRUE.
ageParticle(emptyParticle) = 1
k=k+1
GO TO (820,830,840,850,852,854), k
820 xParticle(emptyParticle) = xTemp + 1
yParticle(emptyParticle) = yTemp
zParticle(emptyParticle) = zTemp
GO TO 860
830 xParticle(emptyParticle) = xTemp - 1
yParticle(emptyParticle) = yTemp
zParticle(emptyParticle) = zTemp
GO TO 860
840 xParticle(emptyParticle) = xTemp
yParticle(emptyParticle) = yTemp + 1
zParticle(emptyParticle) = zTemp
GO TO 860
850 xParticle(emptyParticle) = xTemp
yParticle(emptyParticle) = yTemp - 1
zParticle(emptyParticle) = zTemp
GO TO 860
852 xParticle(emptyParticle) = xTemp
yParticle(emptyParticle) = yTemp
zParticle(emptyParticle) = zTemp + 1
GO TO 860
854 xParticle(emptyParticle) = xTemp
yParticle(emptyParticle) = yTemp
zParticle(emptyParticle) = zTemp - 1
GO TO 860
860 ENDIF
870 END DO
* End release

ENDIF
ENDIF
880 CONTINUE
890 CONTINUE
900 CONTINUE
* Print '(1X,A,I5,4X,A,I8,4X,A,I6,4X,A,I5)',
* C 'Counter:',autoCounter,'Time:',totalTime,'Hits:',

```



```

* C      hitUnits,'Growth Sites:',growthSites
  ENDIF
*      End Growth
680

1000 END DO

  PRINT *,'Breakthrough'

*      Find center of mass:
  xc = 0
  yc = 0
  zc = 0
  DO 1050 vloc=0,height1
690    DO 1045 hloc=0,width1
      DO 1040 zloc=0,depth1
        IF (imageArray(hloc,vloc,zloc).GT.0) THEN
          xc = xc + hloc
          yc = yc + vloc
          zc = zc + zloc
        ENDIF
1040 CONTINUE
1045 CONTINUE
1050 CONTINUE
700    xc = NINT(FLOAT(xc)/FLOAT(numParticles))
    yc = NINT(FLOAT(yc)/FLOAT(numParticles))
    zc = NINT(FLOAT(zc)/FLOAT(numParticles))

    minLength=MIN(xc,yc,zc,(MAX_LENGTH-xc-1),(MAX_LENGTH-yc-1),
C(MAX_LENGTH-zc-1))/2

    DO 1110 i=0,minLength
      DO 1100 vloc=0-i,i
690        DO 1095 hloc=0-i,i
            DO 1090 zloc=0-i,i
              IF (imageArray((xc+hloc),(yc+vloc),(zc+zloc)).GT.0) THEN
                xc = xc + hloc
                yc = yc + vloc
                zc = zc + zloc
                GO TO 1120
              ENDIF
1090 CONTINUE
1095 CONTINUE
1100 CONTINUE
720 1110 CONTINUE
      PRINT *,'Could not find occupied pixel around center of mass'
      STOP

1120 minLength=MIN(xc,yc,zc,(MAX_LENGTH-xc-1),(MAX_LENGTH-yc-1),
C(MAX_LENGTH-zc-1))/2
    LARGEST_BOX_INDEX = 1
    DO WHILE (boxSizes(LARGEST_BOX_INDEX).GE.minLength)
      LARGEST_BOX_INDEX = LARGEST_BOX_INDEX + 1
    END DO
730

    pGroupSize = AINT(FLOAT(numParticles)/FLOAT(numGroups))+1
    DO 1140 vloc=0,height1
      DO 1135 hloc=0,width1
        DO 1130 zloc=0,depth1
          pAge=imageArray(hloc,vloc,zloc)
          IF (pAge.GT.0) THEN
            imageArray(hloc,vloc,zloc)=
C      254-AINT(FLOAT(pAge)/FLOAT(pGroupSize))
740          ELSE
            imageArray(hloc,vloc,zloc)=0
          ENDIF
1130 CONTINUE

```

```

1135 CONTINUE
1140 CONTINUE

PRINT *,'Find best images'

furthest = 0
DO 1160 vloc=0,height1
DO 1155 hloc=0,width1
DO 1150 zloc=0,depth1
IF (imageArray(hloc,vloc,zloc).GT.0) THEN
yTemp = vloc
GO TO 1170
ENDIF
1150 CONTINUE
1155 CONTINUE
1160 CONTINUE
1170 IF (yTemp.GT.furthest) furthest=yTemp

vstart=yTemp

DO 1190 vloc=height1,0,-1
DO 1185 hloc=0,width1
DO 1180 zloc=0,depth1
IF (imageArray(hloc,vloc,zloc).GT.0) THEN
yTemp = vloc
GO TO 1200
ENDIF
1180 CONTINUE
1185 CONTINUE
1190 CONTINUE
1200 IF ((height1-yTemp).GT.furthest) furthest=height1-yTemp

vend=yTemp

DO 1220 hloc=0,width1
DO 1215 vloc=0,height1
DO 1210 zloc=0,depth1
IF (imageArray(hloc,vloc,zloc).GT.0) THEN
xTemp = hloc
GO TO 1230
ENDIF
1210 CONTINUE
1215 CONTINUE
1220 CONTINUE
1230 IF (xTemp.GT.furthest) furthest=xTemp

hstart=xTemp

DO 1250 hloc=width1,0,-1
DO 1245 vloc=0,height1
DO 1240 zloc=0,depth1
IF (imageArray(hloc,vloc,zloc).GT.0) THEN
xTemp = hloc
GO TO 1260
ENDIF
1240 CONTINUE
1245 CONTINUE
1250 CONTINUE
1260 IF ((width1-xTemp).GT.furthest) furthest=width1-xTemp

hend=xTemp

DO 1272 zloc=0,depth1
DO 1271 vloc=0,height1
DO 1270 hloc=0,width1
IF (imageArray(hloc,vloc,zloc).GT.0) THEN
zTemp = zloc
GO TO 1273

```

```

    ENDIF
1270 CONTINUE
1271 CONTINUE
1272 CONTINUE
1273 IF (zTemp.GT.furthest) furthest=zTemp

    dstart=zTemp

    DO 1277 zloc=depth1,0,-1
    DO 1276 vloc=0,height1
    DO 1275 hloc=0,width1
    IF (imageArray(hloc,vloc,zloc).GT.0) THEN
        zTemp = zloc
        GO TO 1278
    ENDIF
1275 CONTINUE
1276 CONTINUE
1277 CONTINUE
1278 IF ((depth1-zTemp).GT.furthest) furthest=depth1-zTemp

    dend=zTemp

    IF (furthest.LT.bestDistance) THEN
        bestDistance=furthest
        DO 1290 vloc=0,height1
        DO 1285 hloc=0,width1
        DO 1280 zloc=0,depth1
        bestImage(hloc,vloc,zloc)=imageArray(hloc,vloc,zloc)
1280 CONTINUE
1285 CONTINUE
1290 CONTINUE
    ENDIF

    IF (numParticles.GT.bestMass) THEN
        bestMass = numParticles
        DO 1330 vloc=0,height1
        DO 1325 hloc=0,width1
        DO 1320 zloc=0,depth1
        heavyImage(hloc,vloc,zloc)=imageArray(hloc,vloc,zloc)
1320 CONTINUE
1325 CONTINUE
1330 CONTINUE
    ENDIF

    PRINT *,'Find mass per radius'

    DO 1340 sizeIndex=LARGEST_BOX_INDEX,NUM_BOX_SIZES
    totalMass(sizeIndex) = 0
    lnBoxSizes(sizeIndex) = ALOG(FLOAT(boxSizes(sizeIndex)))
1340 CONTINUE

    configIdx = 0
    DO 1390 yr=(yc-minLength/2),(yc+minLength/2)
    DO 1385 xr=(xc-minLength/2),(xc+minLength/2)
    DO 1380 zr=(zc-minLength/2),(zc+minLength/2)
    IF (imageArray(xr,yr,zr).GT.0) THEN
        configIdx = configIdx + 1
    DO 1370 sizeIndex=LARGEST_BOX_INDEX,NUM_BOX_SIZES
        mass = 0
        yStart = yr - boxSizes(sizeIndex)
        yEnd = yr + boxSizes(sizeIndex)
        xStart = xr - boxSizes(sizeIndex)
        xEnd = xr + boxSizes(sizeIndex)
        zStart = zr - boxSizes(sizeIndex)
        zEnd = zr + boxSizes(sizeIndex)
        DO 1360 vloc=yStart,yEnd
        DO 1355 hloc=xStart,xEnd

```

```

DO 1350 zloc=zStart,zEnd
temp1=SQRT(FLOAT(vloc-yr)**2+FLOAT(hloc-xr)**2+
C      FLOAT(zloc-zr)**2)
IF (temp1.LE.FLOAT(boxSizes(sizeIndex))) THEN
IF (imageArray(hloc,vloc,zloc).GT.0) mass=mass+1
ENDIF
1350 CONTINUE
1355 CONTINUE
1360 CONTINUE
totalMass(sizeIndex) = totalMass(sizeIndex) + mass
1370 CONTINUE
ENDIF

1380 CONTINUE
1385 CONTINUE
1390 CONTINUE

DO 1400 sizeIndex=LARGEST_BOX_INDEX,NUM_BOX_SIZES
lnTotalMass(sizeIndex) =
C      ALOG(FLOAT(totalMass(sizeIndex))/FLOAT(configIdx))
1400 CONTINUE
900

PRINT *,'Calculating dimension'

LAST_BOX_INDEX = 24
FIRST_BOX_INDEX = LARGEST_BOX_INDEX
j = LAST_BOX_INDEX - LARGEST_BOX_INDEX + 1
sx = 0.0
sy = 0.0
st2 = 0.0
db = 0.0
910
DO 1420 i=FIRST_BOX_INDEX,LAST_BOX_INDEX
sx = sx + lnBoxSizes(i)
sy = sy + lnTotalMass(i)
1420 CONTINUE
ss = FLOAT(LAST_BOX_INDEX - FIRST_BOX_INDEX) + 1.0
sross = sx/ss

DO 1440 i=FIRST_BOX_INDEX,LAST_BOX_INDEX
t = lnBoxSizes(i) - sross
920
st2 = st2 + t*t
db = db + t*lnTotalMass(i)
1440 CONTINUE
db = db/st2
sddb = SQRT(1.0/st2)
intcp = (sy - sx*db)/ss
chi2 = 0.0

DO 1460 i=FIRST_BOX_INDEX,LAST_BOX_INDEX
temp1 = lnTotalMass(i) - intcp - db*lnBoxSizes(i)
930
chi2 = chi2 + temp1*temp1
1460 CONTINUE
sigdat = SQRT(chi2/(ss - 2.0))
sddb = sddb*sigdat

dimList(autoCounter)=db
sdDimList(autoCounter)=sddb
timeMassList(autoCounter)=FLOAT(totalTime)/FLOAT(numParticles)
tissueEffList(autoCounter)=FLOAT(numParticles)/FLOAT(tissueParts)
totalEffList(autoCounter)=FLOAT(numParticles)/FLOAT(totalParts)
940
timeList(autoCounter)=totalTime
massList(autoCounter)=numParticles
tissuePartList(autoCounter)=tissueParts
totalPartList(autoCounter)=totalParts
decayPartList(autoCounter)=numDecayed

PRINT *,'Find minimum path'

```

```

DO 1620 vloc=0,height1
DO 1615 hloc=0,width1
DO 1610 zloc=0,depth1
minPathArray(hloc,vloc,zloc)=0
1610 CONTINUE
1615 CONTINUE
1620 CONTINUE

noProgress = .TRUE.
BreakThrough = .FALSE.

stepIndex = 1
DO 1630 hloc=hstart,hend
DO 1629 zloc=dstart,dend
IF (imageArray(hloc,vstart,zloc).GT.0) THEN
minPathArray(hloc,vstart,zloc)=stepIndex
ENDIF
1629 CONTINUE
1630 CONTINUE

DO 1680 WHILE (.NOT.BreakThrough)
DO 1660 vloc=vstart,vend
DO 1655 hloc=hstart,hend
DO 1650 zloc=dstart,dend
IF (minPathArray(hloc,vloc,zloc).EQ.stepIndex) THEN

bTemp1=(imageArray((hloc+1),vloc,zloc).GT.0)
bTemp2=(minPathArray((hloc+1),vloc,zloc).EQ.0)
IF (bTemp1.AND.bTemp2) minPathArray((hloc+1),vloc,zloc)=
C stepIndex+1

bTemp1=(imageArray((hloc-1),vloc,zloc).GT.0)
bTemp2=(minPathArray((hloc-1),vloc,zloc).EQ.0)
IF (bTemp1.AND.bTemp2) minPathArray((hloc-1),vloc,zloc)=
C stepIndex+1

bTemp1=(imageArray(hloc,(vloc+1),zloc).GT.0)
bTemp2=(minPathArray(hloc,(vloc+1),zloc).EQ.0)
IF (bTemp1.AND.bTemp2) minPathArray(hloc,(vloc+1),zloc)=
C stepIndex+1

bTemp1=(imageArray(hloc,(vloc-1),zloc).GT.0)
bTemp2=(minPathArray(hloc,(vloc-1),zloc).EQ.0)
IF (bTemp1.AND.bTemp2) minPathArray(hloc,(vloc-1),zloc)=
C stepIndex+1

bTemp1=(imageArray(hloc,vloc,(zloc+1)).GT.0)
bTemp2=(minPathArray(hloc,vloc,(zloc+1)).EQ.0)
IF (bTemp1.AND.bTemp2) minPathArray(hloc,vloc,(zloc+1))=
C stepIndex+1

bTemp1=(imageArray(hloc,vloc,(zloc-1)).GT.0)
bTemp2=(minPathArray(hloc,vloc,(zloc-1)).EQ.0)
IF (bTemp1.AND.bTemp2) minPathArray(hloc,vloc,(zloc-1))=
C stepIndex+1

noProgress = .FALSE.
ENDIF
1650 CONTINUE
1655 CONTINUE
1660 CONTINUE

IF (noProgress) THEN
PRINT *,'No Progress Finding Minimum Path'
STOP
ENDIF

```

```

stepIndex=stepIndex+1

vloc = vend
hloc = hstart - 1
DO 1670 WHILE (hloc.LT.hend)
hloc = hloc + 1
zloc=dstart-1
DO 1668 WHILE (zloc.LT.dend)
zloc=zloc+1
IF (minPathArray(hloc,vloc,zloc).NE.0) THEN
BreakThrough = .TRUE.
PRINT *, 'Breakthrough minimum path'
breakPoint = hloc
zbreakPoint = zloc
zloc = dend
hloc = hend
ENDIF
1668 END DO
1670 END DO

1680 END DO

vloc = vend
hloc = breakPoint
zloc = zbreakPoint
pointIndex = 0
stepIndex = minPathArray(hloc,vloc,zloc) - 1
minPathArray(hloc,vloc,zloc) = -1
minPath(pointIndex,0) = hloc
minPath(pointIndex,1) = vloc
minPath(pointIndex,2) = zloc

DO 1720 WHILE (vloc.GT.vstart)
xs = hloc - 1
ys = vloc - 1
zs = zloc - 1
xe = hloc + 1
ye = vloc + 1
ze = zloc + 1
DO 1710 y=ys,ye
DO 1705 x=xs,xe
DO 1700 z=zs,ze
IF (minPathArray(x,y,z).EQ.stepIndex) THEN
minPathArray(x,y,z) = -1
stepIndex = stepIndex - 1
pointIndex = pointIndex + 1
hloc = x
vloc = y
zloc = z
minPath(pointIndex,0) = hloc
minPath(pointIndex,1) = vloc
minPath(pointIndex,2) = zloc
GO TO 1720
ENDIF
1700 CONTINUE
1705 CONTINUE
1710 CONTINUE
1720 END DO

DO 1780 sizeIndex=LARGEST_BOX_INDEX,NUM_BOX_SIZES
eSize = FLOAT(boxSizes(sizeIndex))
occBox = 0
pointLoc = 0
DO 1760 i=0,pointIndex
dx = minPath(i,0) - minPath(pointLoc,0)
dy = minPath(i,1) - minPath(pointLoc,1)
dz = minPath(i,2) - minPath(pointLoc,2)
r1 = SQRT(FLOAT(dx*dx) + FLOAT(dy*dy) + FLOAT(dz*dz))

```

```

    IF (r1.GE.eSize) THEN
      pointLoc = i
      occBox = occBox + 1
    ENDIF
1760 CONTINUE

    IF (pointLoc.LT.pointIndex) occBox=occBox+1

    totalMass(sizeIndex) = occBox
    lnBoxSizes(sizeIndex) = ALOG(FLOAT(boxSizes(sizeIndex)))
    lnTotalMass(sizeIndex) = ALOG(FLOAT(totalMass(sizeIndex)))
1780 CONTINUE

    PRINT *,'Calculating minimum-path dimension'

    LAST_BOX_INDEX = 24
    FIRST_BOX_INDEX = LARGEST_BOX_INDEX
    j = LAST_BOX_INDEX - LARGEST_BOX_INDEX + 1
    sx = 0.0
    sy = 0.0
    st2 = 0.0
    db = 0.0
    DO 1820 i=FIRST_BOX_INDEX, LAST_BOX_INDEX
      sx = sx + lnBoxSizes(i)
      sy = sy + lnTotalMass(i)
1820 CONTINUE
    ss = FLOAT(LAST_BOX_INDEX - FIRST_BOX_INDEX) + 1.0
    sxoss = sx/ss

    DO 1840 i=FIRST_BOX_INDEX, LAST_BOX_INDEX
      t = lnBoxSizes(i) - sxoss
      st2 = st2 + t*t
      db = db + t*lnTotalMass(i)
1840 CONTINUE
    db = db/st2
    sddb = SQRT(1.0/st2)
    intcp = (sy - sx*db)/ss
    chi2 = 0.0

    DO 1860 i=FIRST_BOX_INDEX, LAST_BOX_INDEX
      temp1 = lnTotalMass(i) - intcp - db*lnBoxSizes(i)
      chi2 = chi2 + temp1*temp1
1860 CONTINUE
    sigdat = SQRT(chi2/(ss - 2.0))
    sddb = sddb*sigdat

    mpdimList(autoCounter)=0.0-db
    sdMpdimList(autoCounter)=sddb

    i=autoCounter
    WRITE (16,2250) i,dimList(i),sdDimList(i),
C      mpdimList(i),sdMpdimList(i),timeMassList(i),
C      tissueEffList(i),totalEffList(i),timeList(i),
C      massList(i),tissuePartList(i),
C      totalPartList(i),decayPartList(i)

    PRINT '(1X,A,I5,A,I5)', 'Finished Iteration ',autoCounter,
C      ' out of ',AUTO_ITERATIONS

    IF (autoCounter.LT.AUTO_ITERATIONS) GO TO 10

    CLOSE (UNIT=16)

    denominator = 0.0
    numerator = 0.0
    DO 1880 i=1,AUTO_ITERATIONS
      denominator=denominator+1.0/sdMpdimList(i)**2
      numerator=numerator+mpdimList(i)*(1.0/sdMpdimList(i)**2)
1880 CONTINUE

```

```

1880 CONTINUE
      mpdim=numerator/denominator

      numerator = 0.0
      DO 1890 i=1,AUTO_ITERATIONS
        numerator=numerator+(mpdimList(i)-mpdim)**2
1890 CONTINUE
      sdmpdim=SQRT(numerator/FLOAT(AUTO_ITERATIONS-1))
                                                    1160

      denominator = 0.0
      numerator = 0.0
      DO 1900 i=1,AUTO_ITERATIONS
        denominator=denominator+1.0/sdDimList(i)**2
        numerator=numerator+dimList(i)*(1.0/sdDimList(i)**2)
1900 CONTINUE
      db=numerator/denominator

      numerator = 0.0
      DO 1910 i=1,AUTO_ITERATIONS
        numerator=numerator+(dimList(i)-db)**2
1910 CONTINUE
      sddb=SQRT(numerator/FLOAT(AUTO_ITERATIONS-1))

      numerator = 0.0
      DO 1920 i=1,AUTO_ITERATIONS
        numerator=numerator+timeMassList(i)
1920 CONTINUE
      timeMassAvg=numerator/FLOAT(AUTO_ITERATIONS)
                                                    1180

      numerator = 0.0
      DO 1930 i=1,AUTO_ITERATIONS
        numerator=numerator+(timeMassList(i)-timeMassAvg)**2
1930 CONTINUE
      timeMassSD=SQRT(numerator/FLOAT(AUTO_ITERATIONS-1))

      numerator = 0.0
      DO 1940 i=1,AUTO_ITERATIONS
        numerator=numerator+tissueEffList(i)
1940 CONTINUE
      tissueEffAvg=numerator/FLOAT(AUTO_ITERATIONS)
                                                    1190

      numerator = 0.0
      DO 1950 i=1,AUTO_ITERATIONS
        numerator=numerator+(tissueEffList(i)-tissueEffAvg)**2
1950 CONTINUE
      tissueEffSD=SQRT(numerator/FLOAT(AUTO_ITERATIONS-1))

      numerator = 0.0
      DO 1960 i=1,AUTO_ITERATIONS
        numerator=numerator+totalEffList(i)
1960 CONTINUE
      totalEffAvg=numerator/FLOAT(AUTO_ITERATIONS)
                                                    1200

      numerator = 0.0
      DO 1970 i=1,AUTO_ITERATIONS
        numerator=numerator+(totalEffList(i)-totalEffAvg)**2
1970 CONTINUE
      totalEffSD=SQRT(numerator/FLOAT(AUTO_ITERATIONS-1))
                                                    1210

      numerator = 0.0
      DO 1980 i=1,AUTO_ITERATIONS
        numerator=numerator+FLOAT(timeList(i))
1980 CONTINUE
      timeAvg=numerator/FLOAT(AUTO_ITERATIONS)

      numerator = 0.0
      DO 1990 i=1,AUTO_ITERATIONS
        numerator=numerator+(FLOAT(timeList(i))-timeAvg)**2
                                                    1220

```



```

1990 CONTINUE
    timeSD=SQRT(numerator/FLOAT(AUTO_ITERATIONS-1))

    numerator = 0.0
    DO 2000 i=1,AUTO_ITERATIONS
        numerator=numerator+FLOAT(massList(i))
2000 CONTINUE
    massAvg=numerator/FLOAT(AUTO_ITERATIONS)

    numerator = 0.0
    DO 2010 i=1,AUTO_ITERATIONS
        numerator=numerator+(FLOAT(massList(i))-massAvg)**2
2010 CONTINUE
    massSD=SQRT(numerator/FLOAT(AUTO_ITERATIONS-1))

    numerator = 0.0
    DO 2020 i=1,AUTO_ITERATIONS
        numerator=numerator+FLOAT(tissuePartList(i))
2020 CONTINUE
    tissuePartAvg=numerator/FLOAT(AUTO_ITERATIONS)

    numerator = 0.0
    DO 2030 i=1,AUTO_ITERATIONS
        numerator=numerator+(FLOAT(tissuePartList(i))-tissuePartAvg)**2
2030 CONTINUE
    tissuePartSD=SQRT(numerator/FLOAT(AUTO_ITERATIONS-1))

    numerator = 0.0
    DO 2040 i=1,AUTO_ITERATIONS
        numerator=numerator+FLOAT(totalPartList(i))
2040 CONTINUE
    totalPartAvg=numerator/FLOAT(AUTO_ITERATIONS)

    numerator = 0.0
    DO 2050 i=1,AUTO_ITERATIONS
        numerator=numerator+(FLOAT(totalPartList(i))-totalPartAvg)**2
2050 CONTINUE
    totalPartSD=SQRT(numerator/FLOAT(AUTO_ITERATIONS-1))

    numerator = 0.0
    DO 2060 i=1,AUTO_ITERATIONS
        numerator=numerator+FLOAT(decayPartList(i))
2060 CONTINUE
    decayPartAvg=numerator/FLOAT(AUTO_ITERATIONS)

    numerator = 0.0
    DO 2070 i=1,AUTO_ITERATIONS
        numerator=numerator+(FLOAT(decayPartList(i))-decayPartAvg)**2
2070 CONTINUE
    decayPartSD=SQRT(numerator/FLOAT(AUTO_ITERATIONS-1))

    CALL ITIME(tArray)
    compTime=tArray(3)+tArray(2)*60+tArray(1)*3600-compTime
    PRINT '(1X,A,I10)', 'Execution Time (secs): ', compTime

    OPEN (UNIT=19,FILE='Model.Averages',STATUS='NEW')
    WRITE (19,2200) ' '
    WRITE (19,2200) 'Averages:'
    WRITE (19,2240) 'Fractal Dimension:',db,' +/-',sddb
    WRITE (19,2240) 'Minimum-Path Dimension:',mpdim,' +/-',sdmpdim
    WRITE (19,2240) 'Time/Mass:',timeMassAvg,' +/-',timeMassSD
    WRITE (19,2240) 'Tis. Efficn.:',tissueEffAvg,' +/-',tissueEffSD
    WRITE (19,2240) 'Tot. Efficn.:',totalEffAvg,' +/-',totalEffSD
    WRITE (19,2240) 'Time:',timeAvg,' +/-',timeSD
    WRITE (19,2240) 'Mass:',massAvg,' +/-',massSD
    WRITE (19,2240) 'Tis. Prtcls:',tissuePartAvg,' +/-',tissuePartSD
    WRITE (19,2240) 'Tot. Prtcls:',totalPartAvg,' +/-',totalPartSD
    WRITE (19,2240) 'Dec. Prtcls:',decayPartAvg,' +/-',decayPartSD

```

```

CLOSE (UNIT=19)
OPEN (UNIT=17,FILE='Model.Best',STATUS='NEW')
zloc = depth/2
DO 2120 vloc=0,height1
DO 2110 hloc=0,width2
WRITE (17,2260) bestImage(hloc,vloc,zloc),'T'
2110 CONTINUE
WRITE (17,2260) bestImage(width1,vloc,zloc),'C'
2120 CONTINUE
CLOSE (UNIT=17)

OPEN (UNIT=18,FILE='Model.Heavy',STATUS='NEW')
DO 2140 vloc=0,height1
DO 2130 hloc=0,width2
WRITE (18,2260) heavyImage(hloc,vloc,zloc),'T'
2130 CONTINUE
WRITE (18,2260) heavyImage(width1,vloc,zloc),'C'
2140 CONTINUE
CLOSE (UNIT=18)

OPEN (UNIT=18,FILE='Model3.Heavy',STATUS='NEW')
DO 2160 vloc=0,height1
DO 2155 hloc=0,width2
zloc=depth
DO 2150 WHILE(zloc.GT.0)
zloc=zloc-1
IF (heavyImage(hloc,vloc,zloc).GT.0) GO TO 2152
2150 END DO
2152 WRITE (18,2260) zloc,'T'
2155 CONTINUE
WRITE (18,2260) heavyImage(width1,vloc,zloc),'C'
2160 CONTINUE
CLOSE (UNIT=18)

2200 FORMAT (1X,A)
2210 FORMAT (1X,A,I9)
2220 FORMAT (1X,A,F9.7,1X,A)
2230 FORMAT (1X,A,F9.5)
2240 FORMAT (1X,A,F16.7,A,F16.7)
2250 FORMAT (1X,I3,1X,F6.4,1X,F6.4,1X,F6.4,1X,F6.4,
C F8.5,F8.5,F8.5,I7,I6,I7,I7,I6)
2260 FORMAT (1X,I4,A)
2270 FORMAT (1X,A,A)

```

END

A.8 Stress-Based Remodeling Program

The stress-based remodeling program and supporting functions used in the modeling of arteriovenous network formation are listed below. The program and its functions were written using MATLAB.

A.8.1 Main Routine

```
% This routine remodels a square capillary lattice according
% to a shear-stress dependent rule

% latsize = number of nodes per side
latsize=6;

% s = sensitivity parameter
s=0.05;

% dt = time step
dt=1
tfinal=1000

% d = segment diameter matrix
% Initially, d is the connectivity matrix
d=conmsq(latsize);

% L = segment length matrix
L=d;

size=latsize^2;
G=zeros(size);

% G = segment conductance matrix
G(L~=0)=(d(L~=0).^4)./L(L~=0);

known=[1 size];

pknown=[1 0];

% p = node pressure vector
p=pressure(G,known,pknown);

% Q = segment flow matrix
Q=flow(G,p);

% tau = segment shear stress matrix
% tau0 = segment homeostatic shear stress matrix
tau=zeros(size);
tau0=zeros(size);
tau0(d~=0)=Q(d~=0)./((d(d~=0)).^3);

% Set initial perturbation:
d(1,2)=1.21;
d(2,1)=1.21;
d(1,(latsize+1))=1.19;
d((latsize+1),1)=1.19;

% artern = vector of inflow nodes into previously modified segments
artern=[1];
% perimn = vector of inflow nodes into segments eligible for remodeling
perimn=[2 (latsize+1)];

d45=[1];
d410=[1];
d910=[1];
d915=[1];
```

```

d1415=[1];
d1420=[1];
d1920=[1];
d1925=[1];
60

% Main loop:
% iterns = number of generations for remodeling
for iterns=1:3

% dper = diameter matrix of segments eligible for remodeling
dper=zeros(size);
dper(perimn,:)=d(perimn,:);
dper(:,perimn)=d(:,perimn);
dper(perimn,artern)=zeros(length(perimn),length(artern));
dper(artern,perimn)=zeros(length(artern),length(perimn));
70

% Time stepping loop:
for t=dt:dt:(tfinal*iterns)

% Calculate pressures, flows and shear stresses in all segments:
G(L~=0)=(d(L~=0).^4)./L(L~=0);
p=pressure(G,known,pknown);
Q=flow(G,p);
tau(d~=0)=Q(d~=0)./((d(d~=0)).^3);
80

% Change diameter of eligible segments:
d=d-dper;
dper(dper~=0)=dper(dper~=0).*(1+(s*dt).*(tau(dper~=0)-tau0(dper~=0))./tau0(dper~=0));
d=d+dper;

d45=[d45 d(4,5)];
d410=[d410 d(4,10)];
d910=[d910 d(9,10)];
d915=[d915 d(9,15)];
d1415=[d1415 d(14,15)];
d1420=[d1420 d(14,20)];
d1920=[d1920 d(19,20)];
d1925=[d1925 d(19,25)];
90

end

% Set segment diameter to zero if less than 0.1:
d(d<0.1)=0.*d(d<0.1);
100

% Define new set of eligible segments:
artern=[artern,perimn];
contem=sum(d(perimn,:));
itemp=ones(1,length(contem));
itemp(artern)=zeros(1,length(artern));
contem=itemp & contem;
itemp=1:size;
perimn=itemp(contem);
110

end

```

A.8.2 Supporting Functions

Connectivity Matrix Generation

```
% function to create a connectivity matrix for a square lattice
% arguments: side = number of nodes per side
% returns: connectivity matrix

function C=conmsq(side)

C=zeros(side*side);

for i=0:(side-2)
    for j=1:(side-1)
        k=i*side + j;
        C(k,k+1)=1;
        C(k,k+side)=1;
    end
    k=(i+1)*side;
    C(k,k+side)=1;
    k=side*(side-1) + (i+1);
    C(k,k+1)=1;
end

C=C+C';
```

Pressure Calculation

```
% function to find the pressures in a network
% courtesy of Dr. James Baish, Bucknell University
% arguments: G = conductance matrix,
%    known = vector of nodes at which pressure is known,
%    pknown = vector of known pressures
% returns: pressure vector

function p=pressure(G, known,pknown)

% n=number of nodes
n=length(G);
% i=indices of nodes
i=1:n;
p=0*i;
% all pressures set to zero except known pressures
p(known)=pknown;
% sum conductances over columns (sumG is a vector)
sumG=sum(G);
% subtract sum from main diagonal
A=G-diag(sumG,0);
[x,y]=meshgrid(i,known);
% unknown=indices of unknown pressures
unknown=i(~any(x==y));
% right hand side of matrix equation
B=-G*p';
% right hand side of matrix equation for unknowns only
B=B(unknown);
% left hand side of matrix equation for unknowns only
A=A(unknown,unknown);
% solve matrix equation
p(unknown)=(sparse(A)\sparse(B))';
```

Flow Calculation

```
% function to find the flow through a network
% courtesy of Dr. James Baish, Bucknell University
% arguments: G = conductance matrix, p = pressure vector
% returns: volumetric flow
```

```
function f=flow(G,p)
```

```
% n=number of nodes
n=length(G);
% i,j are indices of all non-zero conductances
[i,j,G]=find(G);
% calculate all pressure differences
dp=p(j)-p(i);
% find flows into each node
f=G' .* dp;
% put result in a sparse matrix
f=sparse(i,j,f,n,n);
```

10

Appendix B

Correlation Dimension Measurements

This appendix contains the fractal dimension measurements of the observed vascular networks in the murine dorsal chamber obtained using the correlation algorithm (see subsection 3.4.3). These measurements are listed separately from the box-counting and sandbox measurements of Chapter 4 because the correlation algorithm was shown to be less accurate than either the box-counting or sandbox algorithms in benchmark tests (see subsection 3.4.4).

Measurements of normal subcutaneous arteriovenous networks in nude mice ($n = 12$) yielded a value of $d_{corr} = 1.71 \pm 0.04$. Measurements of bone-induced arteriovenous networks in nude mice ($n = 10$) yielded a value of $d_{corr} = 1.72 \pm 0.05$. Measurements of normal striated skin muscle capillary networks in nude mice ($n = 12$) yielded a value of $d_{corr} = 2.01 \pm 0.02$. Measurements of human adenocarcinoma LS174T vascular networks in nude mice ($n = 12$) yielded a value of $d_{corr} = 1.94 \pm 0.04$. The results of all these measurements are summarized in Figure B-1. Correlation dimensions measured in C3H mice implanted with three different murine tumor cell lines ($n = 3$ for

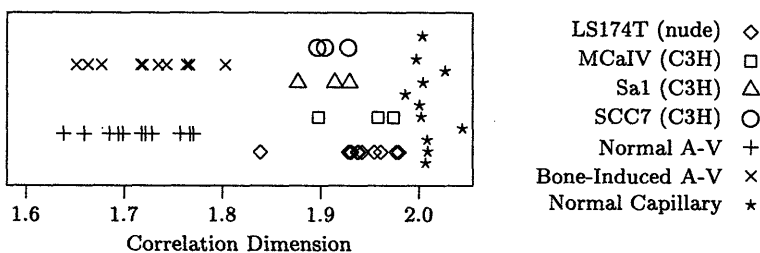


Figure B-1: Correlation dimensions of the observed vascular networks.

Table B.1: Vascular Network Class Separation Based on Correlation Dimension

Network Classes	Correlation Algorithm	
	M-W	t-test
Tumor vs. Capillary	$p < 0.0001$	$p < 0.0001$
Tumor vs. A-V	$p < 0.0001$	$p < 0.0001$
A-V vs. Capillary	$p < 0.0001$	$p < 0.0001$
Bone A-V vs. S.C. A-V	$p = 0.6924$	$p = 0.6006$
Tumor (nude) vs. Tumor (C3H)	$p = 0.0646$	$p = 0.2412$

each) fell within the approximate range of the LS174T measurements (see Figure B-1).

When compared to the values obtained using the box-counting or sandbox algorithms (see Chapter 4), the values obtained by the correlation algorithm are slightly but consistently higher. In order to verify whether the correlation dimension results can also be used to separate the observed vascular networks into three distinct classes of scale-invariant behavior, statistical significance tests were carried out similar to those detailed in subsection 4.4.1. The data from Figure B-1 were divided into five pairs of groups. The first three pairs were used to measure between-class separation and consisted of all possible pairings of the groups:

- Arteriovenous networks — normal subcutaneous and bone-induced networks in nude mice ($n = 22$).
- Tumor networks — tumor networks in nude and C3H mice ($n = 21$).
- Capillary networks — normal capillary networks in nude mice ($n = 12$).

The last two pairs were used to measure within-class separation within the arteriovenous network class and within the tumor network class:

- Bone-induced arteriovenous networks in nude mice ($n = 10$) vs. subcutaneous arteriovenous networks in nude mice ($n = 12$).
- LS174T tumor networks in nude mice ($n = 12$) vs. various tumor networks in C3H mice ($n = 9$).

The results are summarized in Table B.1.

The p -values in Table B.1 show that the correlation dimension clearly separates the three observed classes of two-dimensional vascular networks: normal arteriovenous networks, normal capillary networks, and tumor networks. The p -values in Table B.1 also show that the correlation dimensions of bone-induced and subcutaneous arteriovenous networks are statistically similar. Correlation dimensions for tumor networks in nude mice (LS174T tumors) and tumor networks in C3H mice (MCAIV, SCC7 and Sa1 tumors) are also statistically similar.

The results listed above are in accord with the results obtained using the box-counting and sandbox algorithms in Chapter 4. Therefore, the conclusions reached in Chapter 4 are valid for correlation dimension measurements too.

Appendix C

Fractal Dimensions in Tumor Regression

In subsection 4.2.2 the time dependence of vascular network fractal dimensions during tumor growth was described. As this thesis was nearing completion, a new in vivo hormone-dependent regressing tumor model was being developed in the lab. In this appendix, the fractal dimension measurements from two individual regressing tumors are described. While many of the conclusions are not final due to the small sample size ($n = 2$), some general trends can be discerned.

The tumor line used was Shionogi (SC115) murine mammary carcinoma, whose growth is known to be androgen-dependent [24]. The tumors were grown using the dorsal window preparation in SCID mice. The experimental methods used to grow the tumors, acquire the images, and measure the fractal dimensions were similar to those described in Chapter 3, with one exception. In the experiments described in Chapter 3, a dense tumor cell suspension from cell culture was inoculated onto the dorsal skinfold. In the Shionogi tumor experiments, a piece of tumor tissue (from another animal) having a linear dimension of 2 mm was placed in the dorsal chamber of male mice. This difference was due to the inability to grow the tumor rapidly in the dorsal chamber from a cell suspension.

Preliminary microscopic observations showed that as the tumor grew, blood vessels became larger and more tortuous. After hormone depletion by orchiectomy, tumor microvascular morphology changed markedly. As the tumor shrank, vessel diameters decreased and vessels assumed a more linear appearance. Vessel rarefaction appeared to precede tumor regression.

Fractal dimensions were measured when there was a large enough number of vessel segments in the tumor. Since recordings were not made daily, measurements were performed on images acquired on days 11,15,16,18 after tumor implantation. Orchiectomy was performed on day 14, and the tumor regressed during the days that followed. The measurements were performed for the two

Table C.1: Fractal Dimensions of Regressing Shionogi Tumor Networks

Dimension	day 11	day 15	day 16	day 18
d_{box} (tumor 1)	1.87 ± 0.02	1.85 ± 0.03	1.78 ± 0.01	1.79 ± 0.01
d_{box} (tumor 2)	1.87 ± 0.02	1.91 ± 0.02	1.82 ± 0.03	1.81 ± 0.03
d_{min} (tumor 1)	1.15 ± 0.01	1.12 ± 0.01	1.09 ± 0.01	1.09 ± 0.01
d_{min} (tumor 2)	1.07 ± 0.01	1.08 ± 0.01	1.05 ± 0.01	1.07 ± 0.01

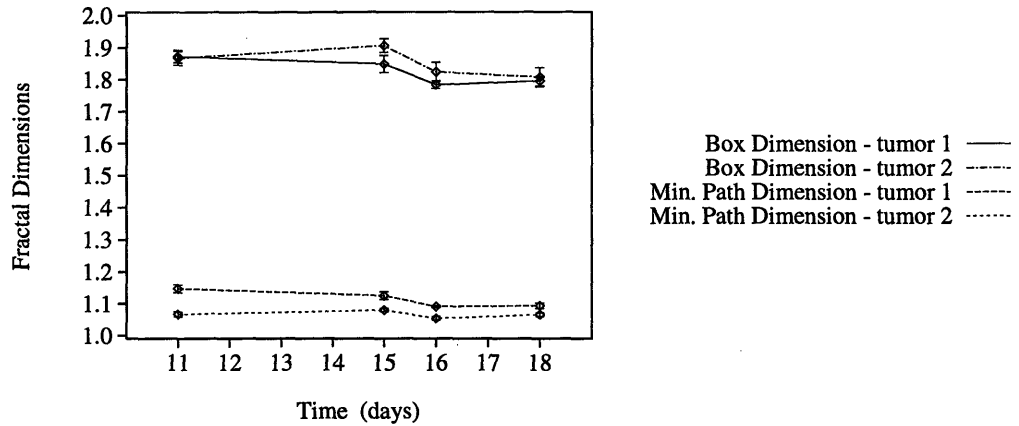


Figure C-1: Fractal dimensions of Shionogi tumor networks during regression. Orchiectomy was performed on day 14, after which the tumors began regressing.

tumors whose optical quality was adequate during all four recording days. The measured values are reported in Table C.1. The values are reported with the standard error of the curve fit. A graphic representation of these results is shown in Figure C-1.

The fractal dimension values measured on day 11, when the tumor was in the growth phase, and on day 15, immediately after orchiectomy, are consistent with the values reported for all other growing tumors (see section 4.2). However, from day 15 to day 16, there is a significant reduction in all fractal dimensions. The decreasing fractal dimension implies that the size of avascular areas increased from day 15 to day 16 (relative to tumor size). This finding is consistent with the observation that vessel rarefaction appeared to precede tumor regression. The decreasing minimum-path dimension is consistent with the observation that vessels appeared to assume a more linear morphology. From day 16 to day 18 there appear to be no statistically significant changes in fractal dimensions. This finding can be interpreted as there having been achieved some sort of balanced rate for vessel resorption and tumor regression. From a scale-invariant vantage, such a balance would maintain the same fractal dimension as the tumor shrank.

The above conclusions are speculative in nature because of the small sample size ($n = 2$) involved. However, they point to one potentially important hypothesis — that the Shionogi tumor networks regress because of vessel resorption (and not vice versa). Measurements in a larger number of tumors are necessary to confirm the aforementioned findings.

Appendix D

In Vitro Verification of Autocrine Mechanism

The growth model for normal capillary networks advanced in Chapter 5 suggested that an autocrine mechanism for growth factor release by endothelial cells is key to normal angiogenesis. In order to corroborate that suggestion, a series of in vitro experiments was designed to examine whether directional dependence in growth factor administration would manifest itself in the morphology of an endothelial cell layer in culture.

While this experiment was being conducted, other investigators published the results of a different experiment which demonstrated more conclusively and elegantly the existence of an autocrine mechanism for angiogenesis [48] (described briefly at the end of section 5.2). It is for this reason that the results of our in vitro experiments are relegated to an appendix, and will be described here in brief only.

In Chapter 5, the autocrine mechanism was proposed to explain the observed absence of gradient sensitive growth during normal angiogenesis. Therefore, it was hypothesized that if growth factor was administered in vitro to an endothelial cell monolayer either in a single dose, which would create a uniform concentration, or by controlled release, which would create a gradient, the morphologic attributes of the layer would be essentially the same in both systems, because the autocrine release of growth factor would “mask” the gradient.

We set out to test this hypothesis by looking at the orientation of endothelial cells in vitro following administration of bFGF. Bovine capillary endothelial cells were prepared and plated on a collagen gel covered with a liquid medium using standard techniques described in the literature [95]. In one set of dishes bFGF in concentrations of 25, 50, or 100 ng/ml was applied topically in one dose 2 days after plating. This procedure assured uniform bFGF concentration throughout the dish. In another set of dishes, a disk approximately 2 mm in diameter composed of heparin sepharose

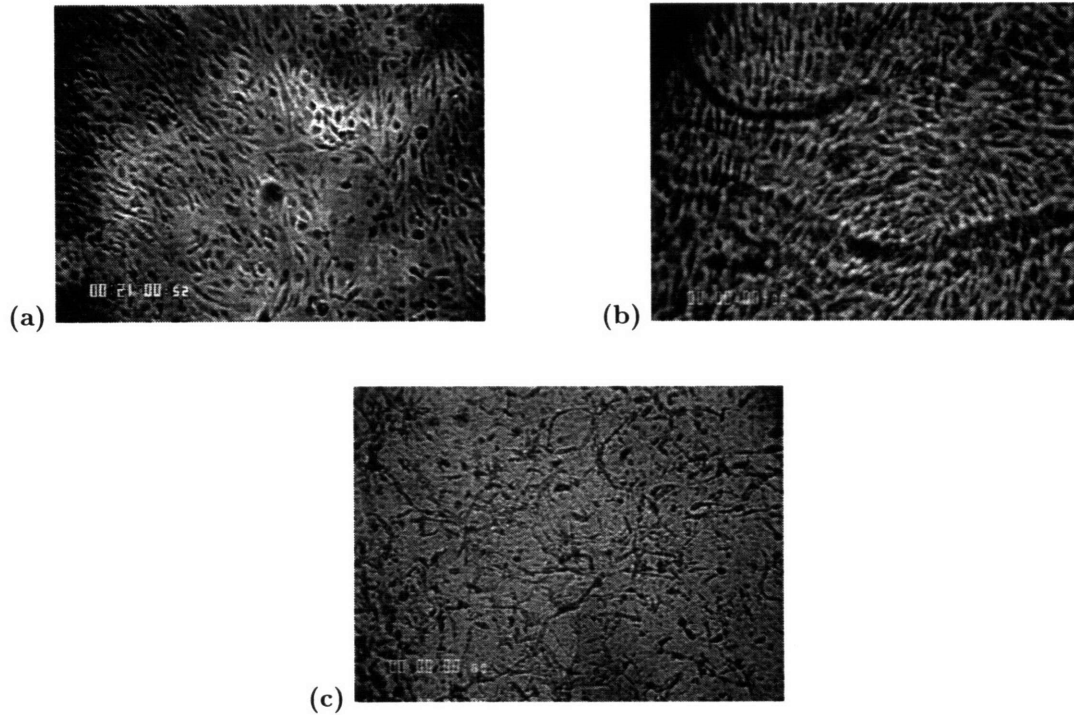


Figure D-1: Morphological archetypes in endothelial cell cultures: (a) Newly plated endothelial cells showing random orientation and typified by cell-less voids; (b) Endothelial cells in vicinity of disk 5 days after plating, showing locally oriented groups of cells yet no global orientation (i.e., it is impossible to discern the location of the disk); (c) Randomly oriented endothelial cell sprouts in a culture where bFGF was topically applied.

coated beads bound with bFGF, was implanted in the periphery of the dish. Since heparin strongly binds bFGF [33], the bFGF was slowly released, thus creating a growth factor gradient across the culture dish. The heparin concentration was adjusted to the level just necessary to elicit visible morphological effects in the endothelial cells.

After approximately a week of transient morphological changes, the endothelial cells achieved a nearly constant morphology, regardless of initial growth factor concentration. This morphology was characterized by dividing the layer into three areas: disk vicinity (“Area 1”), center of dish (“Area 2”), and diametrically opposite the disk (“Area 3”). In dishes without disks corresponding areas were chosen. In each of these areas the morphology of the monolayer and of the sprouts, if any, was described. The monolayer morphology was divided into one of three classes: randomly oriented cells with no directionality, cells in groups of uniform (yet unpredictable) directionality, or cells with a global orientation (as would be observed in gradient-sensitive growth). The sprouts were also visually examined for any preferred orientation, either linear or radial. Results are summarized in Table D.1. The morphological archetypes described in Table D.1 are demonstrated in Figure D-1.

The most important finding was that under no circumstances was global directionality observed in the monolayer of endothelial cells. While groups of cells could be found oriented in a uniform

Table D.1: Morphological Characteristics of Endothelial Cell Cultures

	Controlled Release			Single Dose		
	Area 1	Area 2	Area 3	Area 1	Area 2	Area 3
Monolayer	LO	LO	RO	LO	LO	LO
Sprouts	RO	No sprouts	No sprouts	RO	RO	RO
RO = Randomly oriented, no particular orientation LO = Locally oriented groups, but no global orientation GO = Globally oriented, as would be expected in diffusion-limited growth						

direction (see Figure D-1b), this direction would change randomly from one group to another, thus arguing for the existence of a local mechanism for determining orientation, but little global influence. Furthermore, the orientation of the sprouts (tube-like structures resembling capillaries) was random in all cases that sprouts were observed. A weak directional influence was observed in the dishes with disks since sprouts were found only in the proximity of the disks. However, the lack of global endothelial cell orientation even near the disk seems to argue against gradient-sensitive growth. This observation could be explained by postulating that bFGF levels away from the disk had fallen so much that even the autocrine mechanism could not be triggered beyond a certain distance from the disk.

In summary, the lack of any morphological attributes typical of diffusion-limited growth [131] supports the idea of an autocrine mechanism that “masks” the gradients generated using the heparin sepharose disk system. While these experiments were limited in scope, they represented an important preliminary step in corroborating the predictions of Chapter 5. The recent publication of a more definitive experiment [48] provided unequivocal evidence for an autocrine mechanism underlying endothelial cell proliferation.

Bibliography

- [1] H. Ahlstrom, R. Christofferson, and L. E. Lorelius. Vascularization of the continuous human colonic cancer cell line LS 174 T deposited subcutaneously in nude rats. *APMIS*, 96:701–710, 1988.
- [2] W. E. Allen and D. J. Wilson. Early embryonic angiogenesis in the chick area vasculosa. *J Anat*, 183:579–585, 1993.
- [3] O. Arend, S. Wolf, F. Jung, B. Bertram, H. Pöstgens, H. Toonen, and M. Reim. Retinal microcirculation in patients with diabetes mellitus: Dynamic and morphological analysis of perifoveal capillary network. *Brit J Ophthalmol*, 75:514–518, 1991.
- [4] J. W. Baish. Formulation of a statistical model of heat transfer in perfused tissue. *J Biomech Eng*, 116:521–527, 1994.
- [5] J. W. Baish, Y. Gazit, D. A. Berk, L. T. Baxter, and R. K. Jain. Fractal dimension as a measure of microvascular heterogeneity in tumors: Implications for transport. In *Proc. 42nd Annual Conference of the Microcirculatory Society*, April 1995.
- [6] J. W. Baish, Y. Gazit, D. A. Berk, M. Nozue, L. T. Baxter, and R. K. Jain. An invasion percolation model of architectural obstacles to transport in tumors. *Ann Biomed Eng*, 23:S–28, 1995.
- [7] J. W. Baish, Y. Gazit, D. A. Berk, M. Nozue, L. T. Baxter, and R. K. Jain. Role of tumor vascular architecture in nutrient and drug delivery: An invasion percolation based network model. *Microvasc Res*, In press, 1996.
- [8] D. Balding and D. L. S. McElwain. A mathematical model of tumour-induced capillary growth. *J Theor Biol*, 114:53–73, 1985.
- [9] J. B. Bassingthwaighe, L. S. Liebovitch, and B. J. West. *Fractal Physiology*. Oxford University Press, New York, 1994.

- [10] E. Ben-Jacob, H. Shmueli, O. Shochet, and A. Tenenbaum. Adaptive self-organization during growth of bacterial colonies. *Physica A*, 187:378–424, 1992.
- [11] R. A. O. Bennett, R. N. Pittman, and S. M. Sullivan. Capillary spatial pattern and muscle fiber geometry in three hamster striated muscles. *Am J Physiol*, 260:H579–H585, 1991.
- [12] D. A. Berk, F. Yuan, M. Leunig, and R. K. Jain. Fluorescence photobleaching with spatial Fourier analysis: Measurement of diffusion in light-scattering media. *Biophys J*, 65:2428–2436, 1993.
- [13] P. C. Brooks, A. M. P. Montgomery, M. Rosenfeld, R. A. Reisfeld, T. Hu, G. Klier, and D. A. Cheresh. Integrin $\alpha_v\beta_3$ antagonists promote tumor regression by inducing apoptosis of angiogenic blood vessels. *Cell*, 79:1157–1164, 1994.
- [14] A. Bunde and S. Havlin. A brief introduction to fractal geometry. In A. Bunde and S. Havlin, editors, *Fractals in Science*, pages 1–25. Springer, Berlin, 1994.
- [15] P. H. Burri and M. R. Tarek. A novel mechanism of capillary growth in the rat pulmonary microcirculation. *Anat Rec*, 228:35–45, 1990.
- [16] G. J. Burton and M. E. Palmer. The chorioallantoic capillary plexus of the chicken egg: A microvascular corrosion casting study. *Scanning Microscop*, 3:549–558, 1989.
- [17] N. A. Busch and I. A. Silver. Three dimensional reconstruction of branched tree structures from serial sections. *Adv Exp Med Biol*, 222:77–86, 1988.
- [18] F. Caserta, H. E. Stanley, W. D. Eldred, G. Daccord, R. E. Hausman, and J. Nittmann. Physical mechanisms underlying neurite growth: A quantitative analysis of neuronal shape. *Phys Rev Lett*, 64:95–98, 1990.
- [19] I. I. H. Chen and R. L. Prewitt. A mathematical representation for vessel network. *J Theor Biol*, 98:211–219, 1982.
- [20] S. E. Connolly, T. A. Hores, L. E. H. Smith, and P. A. D’Amore. Characterization of vascular development in the mouse retina. *Microvasc Res*, 36:275–290, 1988.
- [21] P. A. D’Amore. Modes of FGF release in vivo and in vitro. *Cancer Metast Rev*, 9:227–238, 1990.
- [22] G. E. Davis and C. W. Camarillo. Regulation of endothelial cell morphogenesis by integrins, mechanical forces, and matrix guidance pathways. *Exp Cell Res*, 216:113–123, 1995.
- [23] A. Daxer. Fractals and retinal vessels. *Lancet*, 339:618, 1992.

- [24] W. J. Desmond, Jr., S. J. Wolbers., and G. Sato. Cloned mouse mammary cell lines requiring androgens for growth in culture. *Cell*, 8:79–86, 1976.
- [25] M. W. Dewhirst, C. Y. Tso, R. Oliver, C. S. Gustafson, T. W. Secomb, and J. F. Gross. Morphologic and hemodynamic comparison of tumor and healing normal tissue microvasculature. *Int J Rad Oncol Biol Phys*, 17:91–99, 1989.
- [26] E. T. Engelson, T. C. Skalak, and G. W. Schmid-Schonbein. The microvasculature in skeletal muscle. I. Arteriolar networks in rat spinotrapezius muscle. *Microvasc Res*, 30:29–44, 1985.
- [27] K. J. Falconer. *Fractal Geometry: Mathematical Foundations and Applications*. Wiley, Chichester, 1990.
- [28] F. Family, B. R. Masters, and D. E. Platt. Fractal pattern formation in human retinal vessels. *Physica D*, 38:98–103, 1989.
- [29] B. M. Fenton and B. W. Zweifach. Microcirculatory model relating geometrical variations to changes in pressure and flow rate. *Ann Biomed Eng*, 9:303–321, 1981.
- [30] I. J. Fidler and L. M. Ellis. The implications of angiogenesis for the biology and therapy of cancer metastasis. *Cell*, 79:185–188, 1994.
- [31] S. B. Field, I. A. Burney, S. Needham, R. J. Maxwell, J. Coggle, and J. R. Griffiths. Are transplanted tumours suitable as models for studies on vasculature? *Int J Radiat Biol*, 60:255–260, 1991.
- [32] G. F. Fishman and L. R. Moore III. A statistical evaluation of multiplicative random number generators with modulus $2^{31} - 1$. *J Am Stat Assoc*, 77:129–136, 1982.
- [33] J. Folkman. Tumor angiogenesis. In J. F. Holland, E. Frei, R. C. Bast, D. W. Kufe, D. L. Morton, and R. R. Weichselbaum, editors, *Cancer Medicine*, pages 153–170. Lea & Febiger, Philadelphia, 1993.
- [34] J. Folkman. Seminars in medicine of the Beth Israel Hospital, Boston: Clinical applications of research on angiogenesis. *N Engl J Med*, 333:1757–1763, 1995.
- [35] J. Folkman. Tumor angiogenesis. In J. Mendelsohn, P. M. Howley, M. A. Israel, and L. A. Liotta, editors, *The Molecular Basis of Cancer*, pages 206–232. W. B. Saunders, Philadelphia, 1995.
- [36] J. Folkman and Y. Shing. Angiogenesis. *J Biol Chem*, 267:10931–10934, 1992.
- [37] A. W. Fryczkowski and M. D. Sherman. Scanning electron microscopy of human ocular vascular casts: The submacular choriocapillaries. *Acta Anat*, 132:265–269, 1988.

- [38] Y. C. Fung. *Biomechanics: Motion, Flow, Stress, and Growth*. Springer, New York, 1990.
- [39] J. R. Gamble, L. J. Matthias, G. Meyer, P. Kaur, G. Russ, R. Faull, M. C. Berndt, and M. A. Vadas. Regulation of in vitro capillary tube formation by anti-integrin antibodies. *J Cell Biol*, 121:931–943, 1993.
- [40] R. Z. Gan, Y. Tian, R. T. Yen, and G. S. Kassab. Morphometry of the dog pulmonary venous tree. *J Appl Physiol*, 75:432–440, 1993.
- [41] Y. Gazit, J. W. Baish, L. T. Baxter, and R. K. Jain. A model for the formation of arterial networks. *Bull Amer Phys Soc*, 41:429–430, 1996.
- [42] Y. Gazit, D. Berk, M. Leunig, L. T. Baxter, and R. K. Jain. Fractal analysis of two-dimensional normal and tumor vascular networks. *Bull Amer Phys Soc*, 39:596–597, 1994.
- [43] Y. Gazit, D. Berk, M. Leunig, L. T. Baxter, and R. K. Jain. Fractal analysis of two-dimensional normal and tumor vascular networks and its implications. In *Proc. 41st Annual Conference of the Microcirculatory Society*, page 42, April 1994.
- [44] Y. Gazit, D. A. Berk, L. T. Baxter, and R. K. Jain. Vascular network growth modeling based on fractal analysis. *Bull Amer Phys Soc*, 40:411, 1995.
- [45] Y. Gazit, D. A. Berk, M. Leunig, L. T. Baxter, and R. K. Jain. Scale-invariant behavior and vascular network formation in normal and tumor tissue. *Phys Rev Lett*, 75:2428–2431, 1995.
- [46] Y. Gazit, S. Patan, D. Berk, M. Leunig, L. Munn, L. Baxter, and R. K. Jain. New insights into the structure of tumor vasculature: From fractal dimensions to intussusception. *Biorheology*, 32:112, 1995.
- [47] M. E. Gottlieb. Angiogenesis and vascular networks: Complex anatomies from deterministic non-linear physiologies. In J. M. Garcia-Ruiz, E. Louis, P. Meakin, and L. M. Sander, editors, *Growth Patterns in Physical Sciences and Biology*, pages 267–276. Plenum, New York, 1993.
- [48] A. Gualandris, M. Rusnati, M. Belleri, E. E. Nelli, M. Bastaki, M. P. Molinari-Tosatti, F. Bonardi, S. Parolini, A. Albin, L. Morbidelli, M. Ziche, A. Corallini, L. Possati, A. Vacca, D. Ribatti, and M. Presta. Basic fibroblast growth factor overexpression in endothelial cells: An autocrine mechanism for angiogenesis and angioproliferative diseases. *Cell Growth Diff*, 7:147–160, 1996.
- [49] P. M. Gullino. Extracellular compartments of solid tumors. In F. F. Becker, editor, *Cancer: A Comprehensive Treatise*, volume 3, pages 327–354. Plenum, New York, 1975.
- [50] H. J. Herrmann and H. E. Stanley. The fractal dimension of the minimum path in two- and three-dimensional percolation. *J Phys A*, 21:L829–L833, 1988.

- [51] L. Hesse, J. Chofflet, and Y. Le-Mer. Simulation of the growth pattern of the central retinal artery using a fractal modeling technique. *German J Ophthalmol*, 2:116–118, 1993.
- [52] D. E. Hilmas and E. L. Gillette. Morphometric analysis of the microvasculature of tumors during growth and after x-irradiation. *Cancer*, 33:103–110, 1974.
- [53] K. Hori, M. Suzuki, S. Tanda, and S. Saito. In vivo analysis of tumor vascularization in the rat. *Jpn J Cancer Res*, 81:279–288, 1990.
- [54] K. Horsfield and A. Thurlbeck. Relation between diameter and flow in branches of the bronchial tree. *Bull Math Biol*, 43:681–691, 1981.
- [55] H.-J. Hsieh, N.-Q. Li, and J. A. Frangos. Shear stress increases endothelial platelet-derived growth factor mRNA levels. *Am J Physiol*, 260:H642–H646, 1991.
- [56] A. G. Hudetz. Percolation phenomenon: The effect of capillary network rarefaction. *Microvasc Res*, 45:1–10, 1993.
- [57] D. E. Ingber. Fibronectin controls capillary endothelial cell growth by modulating cell shape. *Proc Nat Acad Sci USA*, 87:3579–3583, 1990.
- [58] D. E. Ingber. Extracellular matrix as a solid-state regulator in angiogenesis: Identification of new targets for anti-cancer therapy. *Semin Cancer Biol*, 3:57–63, 1992.
- [59] R. K. Jain. Transport of molecules in the tumor interstitium: A review. *Cancer Res*, 47:3039–3051, 1987.
- [60] R. K. Jain. Determinants of tumor blood flow: A review. *Cancer Res*, 48:2641–2658, 1988.
- [61] R. K. Jain. Delivery of novel therapeutic agents in tumors: Physiological barriers and strategies. *J Natl Cancer Inst*, 81:570–576, 1989.
- [62] R. K. Jain. Barriers to drug delivery in solid tumors. *Sci Am*, 271:58–65, July 1994.
- [63] L. C. Junqueira, J. Carneiro, and J. A. Long. *Basic Histology*. Lange, Los Altos, CA, fifth edition, 1986.
- [64] F. Kallinowski, R. Zander, M. Hoeckel, and P. Vaupel. Tumor tissue oxygenation as evaluated by computerized pO₂ histography. *Int J Rad Oncol Biol Phys*, 19:953–961, 1990.
- [65] G. S. Kassab, C. A. Rider, N. Tang, and Y.-C. B. Fung. Morphometry of pig coronary arterial trees. *Am J Physiol*, 265:H350–H365, 1993.
- [66] M. F. Kiani and A. G. Hudetz. Computer simulation of growth of anastomosing microvascular networks. *J Theor Biol*, 150:547–560, 1991.

- [67] A. Koller, B. Dawant, A. Liu, A. S. Popel, and P. C. Johnson. Quantitative analysis of arteriolar network architecture in cat sartorius muscle. *Am J Physiol*, 253:H154–H164, 1987.
- [68] M. A. Konerding, F. Steinberg, and V. Budach. The vascular system of xenotransplanted tumors — scanning electron and light microscopic studies. *Scanning Microsc*, 3:327–336, 1989.
- [69] N. Koyama, S. Watanabe, M. Tezuka, N. Morisaki, Y. Saito, and S. Yoshida. Migratory and proliferative effect of platelet-derived growth factor in rabbit retinal endothelial cells: Evidence of an autocrine pathway of platelet-derived growth factor. *J Cell Physiol*, 158:1–6, 1994.
- [70] R. Krauss. New technique to demonstrate the network of blood capillaries of the human retina in their three-dimensional arrangement. *Graefe's Arch Clin Exp Ophthalmol*, 228:187–190, 1990.
- [71] G. Landini and G. Mission. Simulation of corneal neovascularization by inverted diffusion limited aggregation. *Invest Ophthalmol Vis Sci*, 34:1872–1875, 1993.
- [72] G. Landini, G. P. Mission, and P. I. Murray. Fractal analysis of the normal human retinal fluorescein angiogram. *Curr Eye Res*, 12:23–27, 1993.
- [73] H. A. Lehr, M. Leunig, M. D. Menger, D. Nolte, and K. Messmer. Dorsal skinfold chamber technique for intravital microscopy in nude mice. *Am J Pathol*, 143:1055–1062, 1993.
- [74] D. E. Lemons, S. Chien, L. I. Crawshaw, S. Weinbaum, and L. M. Jiji. Significance of vessel size and type in vascular heat transfer. *Am J Physiol*, 253:R128–R135, 1987.
- [75] R. Lenormand. Flow through porous media: Limits of fractal patterns. In M. Fleischmann, D. J. Tildesley, and R. C. Ball, editors, *Fractals in the Natural Sciences*, pages 159–168. Princeton University Press, Princeton, 1990.
- [76] J. R. Less, T. C. Skalak, E. M. Sevick, and R. K. Jain. Microvascular architecture in mammary carcinoma: Branching patterns and vessel dimensions. *Cancer Res*, 51:265–273, 1991.
- [77] M. Leunig, F. Yuan, D. A. Berk, L. E. Gerweck, and R. K. Jain. Angiogenesis and growth of isografted bone: Quantitative in vivo assay in nude mice. *Lab Invest*, 71:300–307, 1994.
- [78] M. Leunig, F. Yuan, M. D. Menger, Y. Boucher, A. E. Goetz, K. Messmer, and R. K. Jain. Angiogenesis, microvascular architecture, microhemodynamics, and interstitial fluid pressure during early growth of human adenocarcinoma LS174T in SCID mice. *Cancer Res*, 52:6553–6560, 1992.
- [79] K. Ley, A. R. Pries, and P. Gaehtgens. Topological structure of rat mesenteric microvessel networks. *Microvasc Res*, 32:315–332, 1986.

- [80] H. H. Lipowsky and B. W. Zweifach. Network analysis of microcirculation of cat mesentery. *Microvasc Res*, 7:73–83, 1974.
- [81] F. Mahler, G. Nagel, H. Saner, and F. Kneubuhl. In vivo comparison of the nailfold capillary diameter as determined by using the erythrocyte column and FITC-labelled albumin. *Int J Microcirc Clin Exp*, 2:147–155, 1983.
- [82] M. A. Mainster. The fractal properties of retinal vessels: Embryological and clinical implications. *Eye*, 4:235–241, 1990.
- [83] J. E. Maloney and B. L. Castle. Pressure-diameter relations of capillaries and small blood vessels in frog lung. *Resp Physiol*, 7:150–162, 1969.
- [84] B. Mandelbrot. How long is the coast of Britain? Statistical self-similarity and fractional dimension. *Science*, 156:636–638, 1967.
- [85] B. B. Mandelbrot. *The Fractal Geometry of Nature*. W. H. Freeman, San Francisco, 1982.
- [86] D. Mark and C. Reed. *Inside the Toolbox using THINK Pascal*, volume 1 of *Macintosh Pascal Programming Primer*. Addison-Wesley, Reading, 1991.
- [87] M. Matsushita and H. Fujikawa. Diffusion-limited growth in bacterial colony formation. *Physica A*, 168:498–506, 1990.
- [88] D. S. McLeod, G. A. Luty, S. D. Wajer, and R. W. Flower. Visualization of a developing vasculature. *Microvasc Res*, 33:257–269, 1987.
- [89] P. G. McMenemy and W. J. Krause. Morphological observations on the unique paired capillaries of the opossum retina. *Cell Tissue Res*, 271:461–468, 1993.
- [90] P. Meakin. Diffusion-controlled cluster formation in 2–6-dimensional space. *Phys Rev A*, 27:1495–1507, 1983.
- [91] P. Meakin, I. Majid, S. Havlin, and H. E. Stanley. Topological properties of diffusion limited aggregation and cluster-cluster aggregation. *J Phys A*, 17:L975–L981, 1984.
- [92] F. A. Merchant, S. J. Aggarwal, K. R. Diller, and A. C. Bovik. In-vivo analysis of angiogenesis and revascularization of transplanted pancreatic islets using confocal microscopy. *J Microscop*, 176:262–275, 1994.
- [93] J. W. Miller, A. P. Adamis, D. T. Shima, P. A. D’Amore, R. S. Moulton, M. S. O’Reilly, J. Folkman, H. F. Dvorak, L. F. Brown, B. Berse, T.-K. Yeo, and K.-T. Yeo. Vascular endothelial growth factor/vascular permeability factor is temporally and spatially correlated with ocular angiogenesis in a primate model. *Am J Pathol*, 145:574–584, 1994.

- [94] R. Montesano, L. Orci, and P. Vassalli. In vitro rapid organization of endothelial cells into capillary-like networks is promoted by collagen matrices. *J Cell Biol*, 97:1648–1652, 1983.
- [95] R. Montesano, M. S. Pepper, and L. Orci. Paracrine induction of angiogenesis in vitro by Swiss 3T3 fibroblasts. *J Cell Sci*, 105:1013–1024, 1993.
- [96] D. Moscatelli. High and low affinity binding sites for basic fibroblast growth factor on cultured cells: Absence of a role for low affinity binding in the stimulation of plasminogen activator production by bovine capillary endothelial cells. *J Cell Physiol*, 131:123–130, 1987.
- [97] C. D. Murray. The physiological principle of minimum work. I. The vascular system and the cost of blood volume. *Proc Nat Acad Sci USA*, 12:207–214, 1926.
- [98] T. Nagel, N. Resnick, W. J. Atkinson, C. F. Dewey, Jr., and M. A. Gimbrone, Jr. Shear stress selectively upregulates intercellular adhesion molecule-1 expression in cultured human vascular endothelial cells. *J Clin Invest*, 94:885–891, 1994.
- [99] J. A. Nagy, L. F. Brown, D. R. Senger, N. Lanir, L. van de Water, A. M. Dvorak, and H. F. Dvorak. Pathogenesis of tumor stroma generation: A critical role for leaky blood vessels and fibrin deposition. *Biochim Biophys Acta*, 948:305–326, 1988.
- [100] R. F. Nicosia, R. Tchoa, and J. Leighton. Angiogenesis-dependent tumor spread in reinforced fibrin clot culture. *Cancer Res*, 43:2159–2166, 1983.
- [101] J. Nittmann, G. Daccord, and H. E. Stanley. Fractal growth of viscous fingers: Quantitative characterization of a fluid instability phenomenon. *Nature*, 314:141–144, 1985.
- [102] M. U. Nollert, N. J. Panaro, and L. V. McIntire. Regulation of genetic expression in shear stress-stimulated endothelial cells. *Ann NY Acad Sci*, 665:94–104, 1992.
- [103] S. Patan, L. L. Munn, and R. K. Jain. Intussusceptive microvascular growth in a human colon adenocarcinoma xenograft: A novel mechanism of tumor angiogenesis. *Microvasc Res*, 51:260–272, 1996.
- [104] R. N. Pittman. Influence of microvascular architecture on oxygen exchange in skeletal muscle. *Microcirc*, 2:1–18, 1995.
- [105] M. J. Plyley, G. K. Sutherland, and A. C. Groom. Geometry of the capillary network in skeletal muscle. *Microvasc Res*, 11:161–173, 1976.
- [106] A. S. Popel. Network models of peripheral circulation. In R. Skalak and S. Chien, editors, *Handbook of Bioengineering*, pages 20.1–20.24. McGraw-Hill, New York, 1986.

- [107] R. F. Potter and A. C. Groom. Capillary diameter and geometry in cardiac and skeletal muscle studied by means of corrosion casts. *Microvasc Res*, 25:68–84, 1983.
- [108] R. J. Price, G. K. Owens, and T. C. Skalak. Immunohistochemical identification of arteriolar development using markers of smooth muscle differentiation. *Circ Res*, 75:520–527, 1994.
- [109] R. J. Price and T. C. Skalak. Circumferential wall stress as a mechanism for arteriolar rarefaction and proliferation in a network model. *Microvasc Res*, 47:188–202, 1994.
- [110] R. Rosso, B. Bacchi, and P. La Barbera. Fractal relation of mainstream length to catchment area in river networks. *Water Resour Res*, 27:381–387, 1991.
- [111] J. C. Russ. *The Image Processing Handbook*. CRC Press, Boca Raton, second edition, 1994.
- [112] S. Schröder, M. Brab, G. W. Schmid-Schonbein, M. Reim, and H. Schmid-Schonbein. Microvascular network topology of the human retinal vessels. *Fortschr Ophthalmol*, 87:52–58, 1990.
- [113] L. Schweigerer, G. Neufeld, J. Friedman, J. A. Abraham, J. C. Fiddes, and D. Gospodarowicz. Capillary endothelial cells express basic fibroblast growth factor, a mitogen that promotes their own growth. *Nature*, 325:257–259, 1987.
- [114] T. W. Secomb, R. Hsu, M. W. Dewhirst, B. Klitzman, and J. F. Gross. Analysis of oxygen transport to tumor tissue by microvascular networks. *Int J Rad Oncol Biol Phys*, 25:481–489, 1993.
- [115] E. M. Sevick and R. K. Jain. Geometric resistance to blood flow in solid tumors perfused ex vivo: Effects of tumor size and perfusion pressure. *Cancer Res*, 49:3506–3512, 1989.
- [116] A. A. Shah-Yukich and A. C. Nelson. Characterization of solid tumor microvasculature: A three-dimensional analysis using the polymer casting technique. *Lab Invest*, 58:236–244, 1988.
- [117] T. F. Sherman. On connecting large vessels to small. The meaning of Murray’s law. *J Gen Physiol*, 78:431–453, 1981.
- [118] T. F. Sherman, A. S. Popel, A. Koller, and P. C. Johnson. The cost of departure from optimal radii in microvascular networks. *J Theor Biol*, 136:245–265, 1989.
- [119] Y. Shing, J. Folkman, C. Haudenschild, D. Lund, R. Crum, and M. Klagsburn. Angiogenesis is stimulated by a tumor-derived endothelial cell growth factor. *J Cell Biochem*, 29:275–287, 1985.
- [120] A. C. Shore and J. E. Tooke. Microvascular function in human essential hypertension. *J Hypertens*, 12:717–728, 1994.

- [121] D. Shweiki, A. Itin, D. Soffer, and E. Keshet. Vascular endothelial growth factor induced by hypoxia may mediate hypoxia-initiated angiogenesis. *Nature*, 359:843–845, 1992.
- [122] Y.-J. Shyy, H.-J. Hsieh, S. Usami, and S. Chien. Fluid shear stress induces a biphasic response of human monocyte chemotactic protein 1 gene expression in vascular endothelium. *Proc Natl Acad Sci USA*, 91:4678–4682, 1994.
- [123] T. C. Skalak and G. W. Schmid-Schonbein. The microvasculature in skeletal muscle. IV. A model of the capillary network. *Microvasc Res*, 32:333–347, 1986.
- [124] S. A. Skinner, P. J. M. Tutton, and P. E. O’Brien. Microvascular architecture of experimental colon tumors in the rat. *Cancer Res*, 50:2411–2417, 1990.
- [125] H. Song and K. Tyml. Evidence for sensing and integration of biological signals by the capillary network. *Am J Physiol*, 265:H1235–H1242, 1993.
- [126] H. E. Stanley. Fractals and multifractals: The interplay of physics and geometry. In A. Bunde and S. Havlin, editors, *Fractals and Disordered Systems*, pages 1–49. Springer, Berlin, 1991.
- [127] D. Stauffer and A. Aharony. *Introduction to Percolation Theory*. Taylor & Francis, London, 1992.
- [128] T. Sun, P. Meakin, and T. Jøssang. Minimum energy dissipation and fractal structures of vascular systems. *Fractals*, 3:123–153, 1995.
- [129] A. Timmer, J. W. Oosterhuis, H. S. Koops, D. T. Sleijfer, B. G. Szabo, and W. Timens. The tumor microenvironment: Possible role of integrins and the extracellular matrix in tumor biological behavior of intratubular germ cell neoplasia and testicular seminomas. *Am J Pathol*, 144:1035–1044, 1994.
- [130] P. Vaupel, F. Kallinowski, and P. Okunieff. Blood flow, oxygen and nutrient supply, and metabolic microenvironment of human tumors: A review. *Cancer Res*, 49:6449–6465, 1989.
- [131] T. Vicsek. *Fractal Growth Phenomena*. World Scientific, Singapore, second edition, 1992.
- [132] E. M. Wahl, F. H. Daniels, E. F. Leonard, C. Levinthal, and S. Cortell. A graph theory model of the glomerular capillary network and its development. *Microvasc Res*, 27:96–109, 1984.
- [133] T. A. Witten and L. M. Sander. Diffusion-limited aggregation, a kinetic critical phenomenon. *Phys Rev Lett*, 47:1400–1403, 1981.
- [134] D. F. Zawicki, R. K. Jain, G. W. Schmid-Schoenbein, and S. Chien. Dynamics of neovascularization in normal tissue. *Microvasc Res*, 21:27–47, 1981.

- [135] M. Ziche, L. Morbidelli, G. Alessandri, and P. M. Gullino. Angiogenesis can be stimulated in vivo by a change in GM3:GD3 ganglioside ratio. *Lab Invest*, 67:711–715, 1992.
- [136] B. W. Zweifach and H. H. Lipowsky. Quantitative studies of microcirculatory structure and function. III. Microvascular hemodynamics of cat mesentery and rabbit omentum. *Circ Res*, 41:380–390, 1977.