# Modeling the Propagation of Inflammation in Atherosclerosis

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#### Abstract

Atherosclerosis is an inflammatory disease that can block blood flow in the arteries as the disease progresses. We modeled the development of atherosclerosis with the concentration of monocytes and pro-inflammatory cytokines in three initial conditions: the low, intermediate, and high level of LDL in the intima of the arterial wall. The result of the simulation predicts the behavior of the system. The inflammatory response in the low LDL level scenario decays rapidly; the response from the intermediate LDL level depends on the strength of the stimulus; the high LDL level will proceed to chronic inflammation regardless of the strength of the stimulus. This model can be a good starting point for the future research of atherosclerosis.

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#### 1. Introduction

Inflammation is the process of eliminating pathogens, foreign bodies or necrotic cells in the vascularized tissue. Once the tissue is damaged, the cells surrounding the site of injury release cytokines and other signal molecules to the extracellular space to trigger the immune system. The local capillaries dilate and become more permeable, allowing both leukocytes and plasma proteins to enter the intercellular space. The phagocytes (neutrophils, monocytes, and macrophages) clear the pathogen or cell debris by phagocytosis, which accounts for the antigen recognition of the acquired immunity. The acute inflammation often involves swelling and heat of the affected tissue, and if the inflammation proceeds to chronic inflammation, the tissue can experience permanent change like fibrosclerosis. [1]

In atherosclerosis, the accumulation of low density lipoprotein (LDL) in the intima of the arteries activates the endothelial cells and triggers monocyte recruitment to the intima. After entering the intima, the monocytes convert to macrophages and engulf LDL. The phagocytosis of LDL transform macrocytes into foam cells, which need to be cleared by immune system. At the same time, the pro-inflammatory cytokines also amplify the monocyte recruitment. As atherosclerosis propagates, a fibrous cap forms on top of inflammation site, isolating the system and reducing inflammation. [2] The fibrous cap may break as the inflammation progresses to form thrombus. The thrombus can either stay at the site or travel with blood to block arteries in different parts of the body, leading to heart diseases, stroke, or angina. [3]



Figure 1. Propagation of Atherosclerosis. Image adapted from [4]

According to American Heart Association, heart disease is the leading cause of death in America, which accounts for over 360,000 deaths annually and \$199.6 billion cost in 2012-2013. Stroke is the second-leading cause of death worldwide in 2013, and it causes 0.5 % of death in the US. [5] Although the mortality of the two diseases declined, they still have a great burden on the global health system. [3]

Computational models are currently being explored as a means of integrating predictive modeling technology with patient data to create personalized plans for managing the multifactorial development process of atherosclerosis in patients [6]. Because inflammation is both central to wound healing and a key driver of chronic tissue injury, models of inflammation propagation in atherosclerosis can provide mechanistic insights, explore treatment possibilities

and improved outcomes for individual patients [7]. Our purpose is to model the inflammation process in the atherosclerosis in order to examine how the disturbance of inflammatory parameters affect the propagation of the inflammation.

#### 2. Methods

#### 2.1 Parameterization:

To model the inflammation process in the atherosclerosis, a reaction-diffusion system of equations was utilized to determine the density of monocytes and cytokines in the intima over time[8][2]. The equations for the density of monocytes (M) and cytokines A in the intima over time can be simplified down to three key terms: a recruitment/production term, degradation term, and cell displacement term.

The recruitment of monocytes from the blood flow, promoted by the current inflammatory cytokines density and amplified by the monocyte secretion of inflammatory cytokines, continually increases until the monocyte density reaches a mechanical saturation due to the formation of the fibrous cap. Therefore, the monocyte recruitment was defined as the function  $f_1(A)$  with the following constraint:

$$f_1(A) = \frac{\alpha_1 + \beta_1 A}{1 + A/\tau_1} \left(\frac{Recruitment}{Saturation}\right)$$
(1)

$$\tau_1 > \frac{\alpha_1}{\beta_1} \tag{2}$$

where by  $\alpha_1$  represents the recruitment of monocytes due to the presence of oxidized LDL,  $\alpha_1$  represents the auto-amplification of monocyte recruitment due to the secretion of inflammatory cytokines by the monocytes, and the simplified mechanical saturation is given by the term  $1 + A/\tau_1$ , with  $\tau_1$  representing the characteristic time of fibrous cap formation via smooth muscle cells. The constraint on  $\tau_1$  ensures that  $f_1(A)$  remains an increasing function.

The cytokine production rate per each individual monocyte, promoted by the inflammatory cytokines, can be represented as a ratio of secretion of inflammatory cytokines to the inhibition of that secretion. Therefore, the cytokine production rate per monocyte was defined as the function  $f_2(A)$ :

$$f_2(A) = \frac{\alpha_2 A}{1 + A/\tau_2} \left(\frac{Secretion}{Inhibition}\right)$$
(3)

where  $\alpha_2$  represents the secretion of inflammatory cytokines, and the simplified inhibition of inflammatory cytokine secretion is given by  $1 + A/\tau_2$ , with  $\tau_2$  representing the characteristic

The degradation of monocytes and cytokines can be represented by the term  $\lambda_1 M$  and  $\lambda_2 A$  respectively, where  $\lambda_1$  is the monocyte degradation coefficient and  $\lambda_2$  is the cytokine degradation coefficient. The displacement of monocytes and cytokines over the length of the intima can be represented by  $d_1 \Delta M$  and  $d_2 \Delta A$ , where  $d_1$  is the diffusion coefficient for monocytes,  $d_2$  is the diffusion coefficient for cytokines. The length of the intima is represented by the parameter L. All parameters are assumed to be non-negative in order to accurately reflect the physiology of the system.

To determine the conditions that reflect the various states of the inflammation process, a kinetic model based on mass action kinetics was formed using the following ordinary differential equations:

$$\frac{dM}{dt} = f_1(A) - \lambda_1 M \tag{4}$$

$$\frac{dA}{dt} = f_2(A)M - \lambda_2 A$$

Stability analysis was then performed on the kinetic to highlight the relationship between the variables and how they affect the state of the model (See Appendix: Stability Analysis Calculations for step-by-step calculations). From the results of the stability analysis, the numerical values of the parameters for each case of interest were determined.

#### 2.2 One-dimensional model:

In order to simplify the inflammation process in the atherosclerosis into a onedimensional diffusion process, the assumption was made that the width of the blood vessel wall is infinitesimally small such that the density of monocytes and cytokines across the vessel wall can be considered constant. Therefore the monocyte recruitment function  $f_1(A)$  can be considered a source term, leading to the following reaction-diffusion system of equations for monocyte and cytokine density for the domain of  $x \in [0, L]$ :

$$\frac{\partial M}{\partial t} = d_1 \frac{\partial^2 M}{\partial x^2} + f_1(A) - \lambda_1 M$$

$$\frac{\partial A}{\partial t} = d_2 \frac{\partial^2 A}{\partial x^2} + f_2(A)M - \lambda_2 A$$
(5)

The constant density across the vessel wall also implies no flux across the vessel wall, leading to Neumann boundary conditions for the model. Both the initial monocyte density and cytokine density are considered uniform and represent the steady non-inflammatory state of the system. The initial monocyte is therefore given by the ratio of monocyte recruitment to degradation ( $M(x, 0) = \alpha_1 / \lambda_1$ ), while the initial cytokine density is significantly smaller ( $A(x, 0) = 10^{-3}$ ).

#### 2.3 Two-dimensional model

To represent the inflammation process in the atherosclerosis as a two-dimensional process, no assumption is made about the width of the blood vessel wall. Therefore, the recruitment of monocytes from the blood flow can be described as a boundary condition for the intima and blood flow and not as a source term, leading to the following reaction-diffusion system of equations for monocyte and cytokine density:

$$\frac{\partial M_{\varepsilon}}{\partial t} = d_1 \Delta M_{\varepsilon} - \lambda_1 M_{\varepsilon}$$

$$\frac{\partial A_{\varepsilon}}{\partial t} = d_2 \Delta A_{\varepsilon} + f_2 (A_{\varepsilon}) M_{\varepsilon} - \lambda_2 A_{\varepsilon}$$
(6)

The intima for the model is represented by a rectangle of length L and width  $\varepsilon$ , where the boundary between the intima and the blood flow occurs on the upper side of the model. Therefore, all boundary conditions for the model are homogenous Neumann with the exception of the boundary condition between the blood flow and the intima, given by:

$$\frac{\partial M_{\varepsilon}(x,\varepsilon)}{\partial y} = \frac{f_1(A_{\varepsilon})}{d_1} \varepsilon \text{ for } x \in [0,L]$$
(7)

# **3. Results3.1 Stability Analysis**



Figure 1: Phase planes of the three different cases of stability for the inflammatory process found by examining the intersections of the nullclines derived from Eq. (4). (a) The phase plane for the bistable case, where A and B are stable and C is unstable. (b) The phase plane for the monostable case, where A is unstable and B is stable. (c) The phase plane for the case with no inflammatory reaction, with only a single stable fixed point A.

The results of the stability analysis indicate the following critical values for existence of B and C, and the stability of A (see Appendix: Stability Analysis Calculations).

Existence for B and C: 
$$\frac{\lambda_2}{\alpha_2 \tau_2} = \left( \sqrt{\frac{\beta_1}{\lambda_1} - \frac{\alpha_1}{\tau_1 \lambda_1}} - \sqrt{\frac{\lambda_2}{\alpha_2 \tau_1} - \frac{\alpha_1}{\tau_1 \lambda_1}} \right)^2$$
 (8)

Equilibrium stability: 
$$\frac{\lambda_2}{\alpha_2} = \frac{\alpha_1}{\lambda_1}$$
 (9)

The existence of A is guaranteed for every parameter choice, for it is the equilibrium of a non-inflammatory state for which the density of inflammatory cytokines is zero, leaving the monocyte density as the ratio of monocyte recruitment to monocyte degradation. However, the stability of A is dependent on relation seen in Eq. (9): when the cytokine degradation to recruitment ratio is larger than the monocyte recruitment to degradation ratio, i.e.  $\frac{\lambda_2}{\alpha_2} > \frac{\alpha_1}{\lambda_1}$ , cytokines are degraded faster than the rate at which they are recruited, preventing the auto-amplification phenomenon that results in the chronic inflammation and therefore corresponds to a stable, non-inflammatory state (Fig. 1a, c). However, when  $\frac{\lambda_2}{\alpha_2} < \frac{\alpha_1}{\lambda_1}$ , cytokine recruitment is greater than the degradation, a small increase in cytokine density can stimulate the auto-amplification phenomenon, thus causing A to become unstable (Fig. 1b).

Unlike A, the existence of B and C are not guaranteed for every parameter choice. For B to exist, the condition  $\frac{\lambda_2}{\alpha_2\tau_2} < \left(\sqrt{\frac{\beta_1}{\lambda_1} - \frac{\alpha_1}{\tau_1\lambda_1}} - \sqrt{\frac{\lambda_2}{\alpha_2\tau_1} - \frac{\alpha_1}{\tau_1\lambda_1}}\right)^2$  must be met. When this condition is not met, there are no positive solutions that correspond to a stable inflammatory state (Fig. 1c). However, when the condition has been met, the equilibrium point B will exist and will always correspond to a stable inflammatory state (Fig. 1a,b). Furthermore, when the condition  $\frac{\lambda_2}{\alpha_2} > \frac{\alpha_1}{\lambda_1}$  is also fulfilled, the equilibrium point C will exist and correspond to an unstable state where a large enough perturbation can create chronic inflammation. Therefore, C corresponds to the threshold which must be surpassed in order for the model to exists in a chronic inflammatory state.

Based on the results of the stability analysis, the numerical values for parameters were chosen such that the numerical solutions for both the one and two-dimensional models can replicate the bistable case and the monostable case (Table 1).

D	Value	
Parameter	Bistable System	Monostable System
α1	2	2
$\alpha_2$	7	2
$\lambda_1$	1	1
$\lambda_2$	26	1.95
<i>d</i> <sub>1</sub>	1-D: 1 2-D: 0.001	1-D: 1 2-D: 0.001
<i>d</i> <sub>2</sub>	1-D: 1 2-D: 0.001	1-D: 1 2-D: 0.001
$ au_1$	1	1
$ au_2$	13/2	42/43
$\beta_1$	8	8

Table 1: Numerical values of the parameters for the 1-D and 2-D models. One set of parameters correspond to the values necessary to represent bistable conditions for the model, while the other set of parameters correspond to the values necessary to represent monostable conditions for the model.

The stability can also be analyzed biologically. In Figure. 2, the plot (a) represents the scenario of intermediate cytokine level at time zero. In this situation, the introduction of monocytes into the intima will produce two results: a small number of monocytes will not

sustain the inflammatory response (Fig 2. a); a large number of monocytes triggers chronic inflammation. This is the median risk situation, and one example of this will be the population with elevated blood cholesterol level but has no sign of atherosclerosis. The plot (b) is the high-risk scenario of atherosclerosis where the accumulation of LDL and cytokines is in the alarming level. This high level of LDL will produce a large chemotactic signal, and any number of monocytes will initiate the inflammation. The plot (c) shows the low initial cytokine concentration in healthy population. The intima will not easily inflame because the site will not attract enough monocyte to amplify the inflammation. The monocytes entered intima will cease rapidly and never evolve to the chronic inflammation in plot (b).



#### 3.2 Bistable Conditions: 3.2.1 One-dimensional model

Figure 2: Monocyte and cytokine density for the one-dimensional model under bistable conditions. A small perturbation over  $x \in [45,55]$  does not surpass the threshold requirement for chronic inflamation, and therefore no wave propgation can be seen in the (a) monocyte density and (b) cytokine density. However, a large perturbation over  $x \in [45,55]$  can pass the threshold requirement for chronic inflamation, causing wave propgation that can be seen in the (c) monocyte density and (d) cytokine density.

The bistable condition has two fates: the small surge of monocytes will cease as in Figure. 3 (a)(b); a large surge of monocytes leads to inflammation in Figure.3 (c)(d). There is a delay between the peak of cytokine concentration and the monocyte concentration, indicating the monocytes produce new cytokines in the intima. The small number of monocyte in (a) and (b) cannot produce enough cytokines to sustain the monocyte recruitment, and the existing cytokines degrade and return the intima to healthy state. However, the large number of monocytes in (c) and (d) produces enough cytokines to overcome the degradation, thus producing the inflammation.



#### 3.2.2 Two-dimensional model



Due to the low rate of diffusion, the sustained inflammation is limited to the boundary of arterial lumen and the intima as time to the infinity. This simulation result explains the localization of atherosclerosis in Figure. 1: the inflamed tissue thickens and narrows the artery.

# **3.3 Monostable Conditions: 3.3.1 One-dimensional model**



Figure 4: Monocyte and cytokine density for the one-dimensional model under monostabl; e conditions. A small perturbation over  $x \in [45,55]$  can cause chronic inflamation, causing wave propgation that can be seen in the (a) monocyte density and (b) cytokine density.

When there are no cytokines in the model, the one-dimensional model at monostable conditions remained in an the unstable state that corresponds to no inflammation (Fig. 2b, Fixed Point A)/ However, a small perturbation causes a large surge of monocytes and cytokines, leading to the propogation of waves that represent a stable, chronic inflammatory state (Fig. 2b, Fixed Point B). As seen in Fig. 3(c), (d), there is a delay between the peak of cytokine concentration and the monocyte concentration due to monocyte production of new cytokines, and the intima rapidly reaches a state of inflammation.

#### 3.3.2 Two-dimensional model



Figure 5: Monocyte and cytokine density for the two-dimensional model under monostable conditions. For a small perturbation over  $x \in [45,55]$ , the propogation of waves corresponding to chronic inflammation was observed at (a) t = 0, (b) t = 1, (c) t = 3, (d) t = 5, (e) t = 7, (f) t = 10.

The results of the two-dimensional model agree with the results observed in the onedimensional model. The small perturbation of the model with monostable conditions causes the increase in monocytes, and as seen in Fig. 4, the low rate of diffusion sustaining the inflammation is limited to the boundary of arterial lumen and the intima as time approaches infinity. The simulation result can also explain the localization of atherosclerosis seem in Figure. 1: the inflamed tissue thickens, narrowing the artery.

#### 4. Discussion

According to NIH National Heart, Lung, and Blood Institute, the risk factors for atherosclerosis include smoking, obesity, unhealthy blood cholesterol levels, stress, high serum C-reactive protein level, and family history of early heart disease [8]. The above risk factors are related to both inflammation and abnormal lipid level in blood, and the simulation results of our model match the risk factor. Although the current model is simple and does not cover all factors in the progression of atherosclerosis, this model can potentially help doctors determine the risk of having atherosclerosis quantitatively by comparing the patient's LDL level with the stability points.

The model indicates the development of atherosclerosis is affected by production, diffusion, inhibition, and degradation of leukocytes and pro-inflammatory cytokines, and each of the four terms are affected by the patient's condition. For instance, periodontitis, the infection of

gum, has been linked to cardiovascular diseases. [9] Patients with periodontitis could have activated innate immune system and raise of cytokine level, which can elevate the blood leukocyte level and may promote atherosclerosis. If precise values of the parameters are measured, the model can predict the time delay between a simulation (periodontitis) and the worsen of atherosclerosis. This prediction could be a valuable reference for doctors to determine which therapy, mild or aggressive, should be chosen for certain patients.

There are several ways in which this model can be expanded upon in the future. The model only considers the density of monocytes and cytokines; however, LDL accumulation triggers the monocyte recruitment and is engulfed by macrophages. Because LDL is associated with various arterial diseases, expansion of the model to include LDL density and separate monocyte and macrophage populations to explore their dynamics during the inflammatory process. The model can also be refined to include the injection of anti-inflammatory therapeutics to observe their ability to reduce chronic inflammation.

Due to lack of available data for the parameterization of the model, we decided to only use pseudo-values for our simulation. Though utilizing pseudo-values may limit the quantitative insight the model could provide, the pseudo-values still allow for qualitative analyses. Lack of data also indicates possible directions of future research. For example, in order to obtain the diffusivity of the cytokines in the extracellular space, the researcher must consider the structure of the extracellular matrix, the interaction between cytokines and cells, and the flow of extracellular fluid. In addition, the diffusivity could be different in different tissue or in different diseases, and the small dimension simulated in the model makes a small uncertainty of diffusivity value obvious in the simulation results. By pursuing the accurate measurements of the parameters and expansion of the model, various studies simulations can be performed, and the acquired knowledge can be applied toward understanding the inflammatory process of atherosclerosis and other similar diseases.

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### 6. Appendix

#### 6.1 Stability Analysis Calculations

To determine the conditions that reflect the various states of the inflammation process, a kinetic model based on mass action kinetics was formed using Eq.(4)

$$\frac{dM}{dt} = f_1(A) - \lambda_1 M$$
$$\frac{dA}{dt} = f_2(A)M - \lambda_2 A$$

Therefore, the null-clines can be determined as follows:

$$0 = f_1(A) - \lambda_1 M \to M = \frac{f_1(A)}{\lambda_1}$$
$$0 = f_2(A)M - \lambda_2 A \to M = \frac{\lambda_2 A}{f_2(A)}$$

Setting the null-clines equal produces the following:  $f(A) = \frac{1}{2} A$ 

$$\begin{split} \frac{\lambda_{1}(A)}{\lambda_{1}} &= \frac{\lambda_{2}A}{f_{2}(A)} \rightarrow \\ 0 &= \frac{\lambda_{2}A(1 + A/\tau_{2})}{\alpha_{2}A} - \frac{\alpha_{1} + \beta_{1}A}{\lambda_{1}(1 + A/\tau_{1})} \rightarrow \\ 0 &= \frac{\lambda_{2}(1 + A/\tau_{1})(1 + A/\tau_{2})}{\alpha_{2}} - \frac{\alpha_{1}}{\lambda_{1}} - \frac{\beta_{1}A}{\lambda_{1}} \rightarrow \\ 0 &= \frac{\lambda_{2}}{\alpha_{2}} \left(1 + A\left(\frac{1}{\tau_{1}} + \frac{1}{\tau_{2}}\right) + \frac{A^{2}}{\tau_{1}\tau_{2}}\right) - \frac{\alpha_{1}}{\lambda_{1}} - \frac{\beta_{1}A}{\lambda_{1}} \rightarrow \\ 0 &= \frac{\lambda_{2}}{\alpha_{2}} + A\left(\frac{\lambda_{2}}{\alpha_{2}}\left(\frac{1}{\tau_{1}} + \frac{1}{\tau_{2}}\right) - \frac{\beta_{1}}{\lambda_{1}}\right) + \frac{\lambda_{2}}{\alpha_{2}}\frac{A^{2}}{\tau_{1}\tau_{2}} - \frac{\alpha_{1}}{\lambda_{1}} \\ 0 &= \frac{\lambda_{2}}{\alpha_{2}\tau_{1}\tau_{2}}A^{2} + \left(\frac{\lambda_{2}}{\alpha_{2}}\left(\frac{1}{\tau_{1}} + \frac{1}{\tau_{2}}\right) - \frac{\beta_{1}}{\lambda_{1}}\right)A + \left(\frac{\lambda_{2}}{\alpha_{2}} - \frac{\alpha_{1}}{\lambda_{1}}\right)A \end{split}$$

which is a quadratic of the form  $ax^2 + bx + c = 0$  where

$$a = \frac{\lambda_2}{\alpha_2 \tau_1 \tau_2}, \qquad b = \left(\frac{\lambda_2}{\alpha_2} \left(\frac{1}{\tau_1} + \frac{1}{\tau_2}\right) - \frac{\beta_1}{\lambda_1}\right), \qquad c = \left(\frac{\lambda_2}{\alpha_2} - \frac{\alpha_1}{\lambda_1}\right)$$

Solving for only nonnegative solutions, critical values are elucidated as the following:

Critical Value for existence: 
$$\frac{\lambda_2}{\alpha_2 \tau_2} = \left( \sqrt{\frac{\beta_1}{\lambda_1} - \frac{\alpha_1}{\tau_1 \lambda_1}} - \sqrt{\frac{\lambda_2}{\alpha_2 \tau_1} - \frac{\alpha_1}{\tau_1 \lambda_1}} \right)^2$$
  
Critical Value for equilibrium stability  $\frac{\lambda_2}{\alpha_2} = \frac{\alpha_1}{\lambda_1}$ 

# 6.2 MATLAB Code:

### 6.2.1 One-dimensional model

% Degredation constnats for immune cells and cytokines respecticely. lambda\_1 = 1; lambda\_2 = 1.95;

% lambda\_2 = 26; % Stable % lambda\_2 = 1; % Unstable

% Recruitment of monocytes due to the presence of ox-LDL, promoted by % endothelial adhesion molecules, chemoattractants and growth factors.  $alpha_1 = 2;$ 

% alpha\_2 .\* A represents the secretion of pro-inflammatory cytokines promoted % by the pro-inflammatory cytokines themselves alpha\_2 = 1;

% alpha\_2 = 7; % Stable % alpha\_2 = 1; % Unstable

% Characteristic time for the fibrous cap formation  $tau_1 = 1$ ;

% Characteristic time for inhibition of the pro-inflammatory cytokines
% secretion mediated by the anti-inflammatory cytokines to act.
tau\_2 = (42./43);
% tau\_2 = (13./2); % Stable
% tau\_2 = (42./43); % Unstable

% Represents the auto-amplification of the recruitment of monocytes% due to the inflammatory cytokines secreted by the monocytes themselves

beta = 8;

% The function  $f_1(A)$  models recruitment of the immune cells from the % blood flow, promoted by the inflammatory cytokines  $f_1 = @(A) (alpha_1 + beta .* A)./(1 + A./tau_1);$ 

% The term  $f_2(A)$ .\* M models the cytokines production rate  $f_2 = @(A) (alpha_2 .* A)./(1 + A./tau_2);$ 

```
% Perturbation
pert = 0.25;
A_pert = 1 * (1 + pert);
M_{pert} = 1 * (1 + pert);
% Initial Conditions
M 0 = alpha 1 ./ lambda 1;
A_0 = 1 .* 10^{-3};
%% PDE Solution 1-D
close all
tstart = 0;
xstart = 0;
xfinal = 100;
tfinal = 100;
numpoints = 201;
tmesh = linspace(tstart,tfinal,numpoints);
xmesh = linspace(xstart,xfinal,numpoints);
% Solution
sol = pdepe(0,@pdefun,@ic,@bc,xmesh,tmesh);
M_{sol} = sol(:,:,1);
A_{sol} = sol(:,:,2);
figure(1)
surf(tmesh,xmesh,M_sol','EdgeColor','none')
title('Monocyte Density')
xlabel('t')
ylabel('x')
```

zlabel('M(x,t)')

```
axis([tstart tfinal xstart xfinal 0 10])
```

```
figure(2)
surf(tmesh,xmesh,A_sol','EdgeColor','none')
title('Cytokine Density')
xlabel('t')
```

ylabel('x') zlabel('A(x,t)')axis([tstart tfinal xstart xfinal 0 10]) % For stability a = linspace(0, 10, numpoints);m = linspace(0, 10, numpoints);dMdt = @(A, M) f 1(A) - lambda 1.\* M; $dAdt = @(A, M) f_2(A) .* M - lambda_2 .* A;$ [Amesh, Mmesh] = meshgrid(a, m); [X\_null\_m, Y\_null\_m] = getNullcline(dMdt(Amesh, Mmesh), a, m); [X\_null\_a, Y\_null\_a] = getNullcline(dAdt(Amesh, Mmesh), a, m); [xint, yint] = getCrossings(X null m, Y null m, X null a, Y null a); figure(3) hold on plot(X null m, Y null m) plot(X\_null\_a, Y\_null\_a) xlabel('A') ylabel('M') title('Stability Phase Plane: Monostable Case') axis([-.5 10 -.5 10]) lgnd = {'Nullcline @ dM/dt = 0', 'Nullcline @ dA/dt = 0'};  $c = \{ 'A', 'B', 'C' \};$ for i = 1:length(xint)  $lgnd{i+2} = sprintf('Fixed Point %s @ (%.2f, %.2f)', c{i}, ...$ xint(i), yint(i)); plot(xint(i), yint(i), 'x', 'MarkerSize', 10) J = getJacobian(Amesh, Mmesh, dMdt(Amesh, Mmesh), dAdt(Amesh, Mmesh), ... xint(i), yint(i)); fprintf('Fixed Point %s @ (%.2f, %.2f)\n', c{i}, xint(i), yint(i)) disp(eig(J))end legend(lgnd, 'Location', 'Best') hold off

```
%%%%% PDE ASSOCIATED FUNCTIONS %%%%%
function [c,f,s] = pdefun(x,t,u,DuDx)
global d_1 d_2 lambda_1 lambda_2 f_1 f_2
```

c = [1; 1];  $f = [d_1; d_2] .* DuDx;$   $S_1 = f_1(u(2)) - lambda_1 .* u(1);$   $S_2 = f_2(u(2)).*u(1) - lambda_2 .* u(2);$  $s = [S_1; S_2];$ 

end

% ------% Initial Conditions function u0 = ic(x) global M\_pert A\_pert M\_0 A\_0 u0 = [M\_0; A\_0].\*([M\_pert;A\_pert].\*((x>=45) && (x<=55)) + 1); end % ------% Boundry Conditions function [pl,ql,pr,qr] = bc(xl,ul,xr,ur,t) pl = [0; 0]; ql = [1; 1]; pr = [0; 0]; qr = [1; 1]; end

#### 6.2.2 Two-dimensional model

%% Setup clear all global epsilon N alpha\_1 lambda\_1 lambda\_2 d\_1 d\_2 f\_1 f\_2 A\_pert M\_pert M\_0 A\_0 L = 1; epsilon = 10^-3;

% Diffusion (or cell displacement) constants  $d_1 = 10^{-3}$ ;  $d_2 = 10^{-3}$ ;

% Degredation constnats for immune cells and cytokines respecticely. lambda\_1 = 1; lambda\_2 = 1.95;

% lambda\_2 = 26; % Stable % lambda\_2 = 1; % Unstable

% Recruitment of monocytes due to the presence of ox-LDL, promoted by % endothelial adhesion molecules, chemoattractants and growth factors.  $alpha_1 = 2;$ 

% alpha\_2 .\* A represents the secretion of pro-inflammatory cytokines promoted % by the pro-inflammatory cytokines themselves alpha\_2 = 1; % alpha\_2 = 7; % Stable % alpha\_2 = 1; % Unstable

% Characteristic time for the fibrous cap formation  $tau_1 = 1$ ;

% Characteristic time for inhibition of the pro-inflammatory cytokines
% secretion mediated by the anti-inflammatory cytokines to act.
tau\_2 = (42./43);
% tau\_2 = (13./2); % Stable
% tau\_2 = (42./43); % Unstable

% Represents the auto-amplification of the recruitment of monocytes % due to the inflammatory cytokines secreted by the monocytes themselves beta = 8;

% The function  $f_1(A)$  models recruitment of the immune cells from the % blood flow, promoted by the inflammatory cytokines  $f_1 = @(A) (alpha_1 + beta .* A)./(1 + A./tau_1);$ 

% The term  $f_2(A)$ .\* M models the cytokines production rate  $f_2 = @(A) (alpha_2 .* A)./(1 + A./tau_2);$ 

pert = .25; A\_pert = 1 \* (1 + pert); M\_pert = 1 \* (1 + pert); M\_0 = alpha\_1 ./ lambda\_1; A\_0 = 1 .\* 10^-6; %% PDE Solution 2-D close all tstart = 0; tfinal = 10;

n = 100 + 1; tmesh = linspace(tstart,tfinal,n);

N = 2; model = createpde(N);

rectangle = [3; 4; 0; L; L; 0; 0; 0; epsilon; epsilon]; geometryFromEdges(model,decsg(rectangle));

G = [0;0];

applyBoundaryCondition(model,'neumann','edge',[1,2 4],'g', G);

applyBoundaryCondition(model,'neumann','edge',3,'g', @bc);

d = [1; 1]; c = [d\_1; d\_2]; a = [lambda\_1; lambda\_2];

specifyCoefficients(model,'m',0,'d',d,'c',c,'a',a,'f',@fcoeffunction); setInitialConditions(model,@ic);

generateMesh(model, 'Hmax', 0.01);
results = solvepde(model, tmesh); % for stationary problems

```
u = results.NodalSolution;
```

```
time_points = [1:10:101];
for j = 1:length(time_points)
    i = time_points(j);
    figure(j);
    hold on
    subplot(2,1,1)
    pdeplot(model,'XYData',u(:, i),'Mesh','on')
    colormap('jet');
    xlabel('x');
    ylabel(sprintf('\\epsilon'));
    xlim([0, L]);
    ylim([0, epsilon]);
    zlabel('M(x,t)');
    title(sprintf('Monocyte Density\nTime: %.1f', results.SolutionTimes(i)))
```

```
subplot(2,1,2)
pdeplot(model,'XYData',u(:, i),'ZData',u(:, i),'Mesh','on')
colormap('jet');
xlabel('x');
ylabel(sprintf('\\epsilon'));
xlim([0, L]);
ylim([0, epsilon]);
zlabel('M(x,t)');
hold off
```

end

%%%%% PDE ASSOCIATED FUNCTIONS %%%%% function f = fcoeffunction(region,state) global f\_2 N = 2; % Number of equations nr = length(region.x); % Number of columns

```
f = zeros(N,nr); % Allocate f
f(1, :) = 0;
f(2, :) = f_2(state.u(2, :)).*state.u(1, :);
end
% _____
% Initial Conditions
function uinit = ic(locations)
global M_pert A_pert M_0 A_0
M = length(locations.x);
uinit = zeros(2,M);
uinit(1,:) = M_0.*(M_pert.*((locations.x>=.45) & (locations.x<=.55))+1);
uinit(2,:) = A_0.*(A_pert.*((locations.x>=.45) \& (locations.x<=.55))+1);
end
% -----
% Boundry Conditions
function bcMatrix = bc(region,state)
global d_1 f_1 epsilon
bcMatrix = [epsilon.*f 1(state.u(2, :))./d 1; 0];
```

```
end
```

## 6.2.3 Obtained from BENG 260:

```
function [X,Y] = getNullcline(d,x,y)
%[X,Y] = getNullcline(d,x,y)
%
% getNullcline takes a matrix, the x and y scales, and returns the x and y
% values of the null-cline.
%
% Simplification of getContours to do only the null-cline
%
%Parameters:
% d : A matrix approximating a two-dimensional function.
\% x: The x-values for the columns of f.
\% y : The y-values for the rows of f.
% [X,Y]: The x and y values of the null-cline.
cn = contourc(x, y, d, [0 0]);
len = cn(2, 1);
X = cn(1, 2:1+len);
Y = cn(2, 2:1+len);
function c = getContours(d,x,y,V)
% c = getContours(f,x,y,V)
%
% getContours takes a function and a set of contour values, and returns the
% x and y values of that contour.
%
```

#### % Parameters:

```
% f : A matrix approximating a two-dimensional function.
```

% x: The x-values for the columns of f.

```
% y : The y-values for the rows of f.
```

```
% V : A vector of desired contour values.
```

```
% c : If length(V) = 1, c(1,:) and c(2,:) are the x and y values of
```

- % the contour. Otherwise, c is a cell, and  $c{i}(1,:)$  and
- %  $c{i}(2,:)$  are the x and y values of the ith contour.

```
Vflag = 0;
if(length(V) == 1)
  V = [V V];
  Vflag = 1;
end
cn = contourc(x,y,d,V);
lencn = size(cn, 2);
lenV = length(V);
c = cell(1,max([2 lenV]));
done = 0;
next = 1;
indcn = 1;
nextorder = 0;
lastheight = nan;
while(~done)
  len = cn(2,indcn);
  height = cn(1,indcn);
  poly = cn(:,indcn+1:indcn+len);
  if(height ~= lastheight)
    nextorder = nextorder + 1;
    lastheight = height;
  end
  c{next} = poly;
  next = next + 1;
  indcn = indcn + len + 1;
  if(indcn \ge lencn)
     done = 1;
  end
end
if(Vflag)
  c = c\{1\};
end
function J = getJacobian(x,y,f,g,x0,y0)
% J = getJacobian(x,y,f,g,x0,y0)
%
```

% getJacobian takes a grid of derivative values and a point in phase space,

% and returns the Jacobian around that point.

%

%Parameters:

% x : The x-values of f and g.
% y : The y-values of f and g.
% f : A matrix approximating the derivative wrt x.

- %~~g~ : A matrix approximating the derivative wrt y.
- % x0 : The x-value for the point.
- % y0 : The y-value for the point.

%

%Jacobian output:

- % J(1,1): Derivative of f wrt x evaluated at x0, y0.
- % J(1,2): Derivative of f wrt y evaluated at x0, y0.
- % J(2,1): Derivative of g wrt x evaluated at x0, y0.
- % J(2,2): Derivative of g wrt y evaluated at x0, y0.

dx = gradient(x); [temp dy] = gradient(y); [dfx dfy] = gradient(f); [dgx dgy] = gradient(g);

```
x = flatten(x);

y = flatten(y);

dx0 = griddata(x,y,flatten(dx),x0,y0);

dy0 = griddata(x,y,flatten(dy),x0,y0);

dfdx0 = griddata(x,y,flatten(dfx),x0,y0);

dfdy0 = griddata(x,y,flatten(dfy),x0,y0);

dgdx0 = griddata(x,y,flatten(dgx),x0,y0);

dgdy0 = griddata(x,y,flatten(dgy),x0,y0);
```

dx0; dy0; dfdx0; dfdy0; dgdx0; dgdy0;

J = [dfdx0/dx0 dfdy0/dy0; dgdx0/dx0 dgdy0/dy0];end

```
function x = flatten(x)
% y = flatten(x)
%
%flatten compresses all data to one dimension
x = squeeze(x(1:numel(x)));
end
```

```
function [xi, fxi] = getCrossings(x1,fx1,x2,fx2)
% pos = getCrossings(x1,fx1,x2,fx2)
%
% getCrossings approximates the places where two functions cross. pos(1,:)
% and pos(2,:) are the x and y coordinates of those crossing points.
```

```
[xi fxi] = intersections(x1,fx1,x2,fx2);
end
```

function [x0,y0] = intersections(x1,y1,x2,y2)

%INTERSECTIONS Intersections of curves.

% Computes the (x,y) locations where two curves intersect. The curves

% can be broken with NaNs or have vertical segments.

%

% Example:

% [X0,Y0] = intersections(X1,Y1,X2,Y2,ROBUST);

%

% where X1 and Y1 are equal-length vectors of at least two points and

% represent curve 1. Similarly, X2 and Y2 represent curve 2.

% X0 and Y0 are column vectors containing the points at which the two

% curves intersect.

%

% ROBUST (optional) set to 1 or true means to use a slight variation of the

% algorithm that might return duplicates of some intersection points, and

% then remove those duplicates. The default is true, but since the

% algorithm is slightly slower you can set it to false if you know that

% your curves don't intersect at any segment boundaries. Also, the robust

% version properly handles parallel and overlapping segments.

%

% The algorithm can return two additional vectors that indicate which

% segment pairs contain intersections and where they are:

%

% [X0,Y0,I,J] = intersections(X1,Y1,X2,Y2,ROBUST);

%

% For each element of the vector I, I(k) = (segment number of (X1,Y1)) +

% (how far along this segment the intersection is). For example, if I(k) =

% 45.25 then the intersection lies a quarter of the way between the line

% segment connecting (X1(45),Y1(45)) and (X1(46),Y1(46)). Similarly for

% the vector J and the segments in (X2, Y2).

%

% You can also get intersections of a curve with itself. Simply pass in % only one curve, i.e.,

%

% [X0,Y0] = intersections(X1,Y1,ROBUST);

%

% where, as before, ROBUST is optional.

% Version: 1.10, 25 February 2008

% Author: Douglas M. Schwarz

% Email: dmschwarz=ieee\*org, dmschwarz=urgrad\*rochester\*edu

% Real\_email = regexprep(Email, {'=','\*'}, {'@','.'})

% Theory of operation:

%

% Given two line segments, L1 and L2,

%

% L1 endpoints: (x1(1),y1(1)) and (x1(2),y1(2))

% L2 endpoints: (x2(1),y2(1)) and (x2(2),y2(2))

%

% we can write four equations with four unknowns and then solve them. The

% four unknowns are t1, t2, x0 and y0, where (x0,y0) is the intersection of

% L1 and L2, t1 is the distance from the starting point of L1 to the

% intersection relative to the length of L1 and t2 is the distance from the

% starting point of L2 to the intersection relative to the length of L2. %

% So, the four equations are %

% (x1(2) - x1(1))\*t1 = x0 - x1(1)

- % (x2(2) x2(1))\*t2 = x0 x2(1)
- % (y1(2) y1(1))\*t1 = y0 y1(1)

% (y2(2) - y2(1))\*t2 = y0 - y2(1)

%

% Rearranging and writing in matrix form,

%

% [x1(2)-x1(1) 0 -1 0; [t1; [-x1(1);  $x^{2}(2)-x^{2}(1) -1 \quad 0; \quad * \quad t^{2}(2) = -x^{2}(1);$ % 0 % 0 0 -1; x0; -y1(1); y1(2)-y1(1) $y_2(2)-y_2(1) = 0 -1$ % 0 y0] -y2(1)] %

% Let's call that  $A^*T = B$ . We can solve for T with  $T = A \setminus B$ . %

% Once we have our solution we just have to look at t1 and t2 to determine % whether L1 and L2 intersect. If  $0 \le t1 \le 1$  and  $0 \le t2 \le 1$  then the two % line segments cross and we can include (x0,y0) in the output. %

% In principle, we have to perform this computation on every pair of line % segments in the input data. This can be quite a large number of pairs so % we will reduce it by doing a simple preliminary check to eliminate line % segment pairs that could not possibly cross. The check is to look at the % smallest enclosing rectangles (with sides parallel to the axes) for each % line segment pair and see if they overlap. If they do then we have to % compute t1 and t2 (via the A\B computation) to see if the line segments % cross, but if they don't then the line segments cannot cross. In a % typical application, this technique will eliminate most of the potential

% line segment pairs.

% x1 and y1 must be vectors with same number of points (at least 2).

if sum(size(x1) > 1) ~= 1 || sum(size(y1) > 1) ~= 1 || length(x1) ~= length(y1) error('X1 and Y1 must be equal-length vectors of at least 2 points.') end

% x2 and y2 must be vectors with same number of points (at least 2). if  $sum(size(x2) > 1) \sim = 1 \parallel sum(size(y2) > 1) \sim = 1 \parallel length(x2) \sim = length(y2)$ 

error('X2 and Y2 must be equal-length vectors of at least 2 points.') end

% Force all inputs to be column vectors.

x1 = x1(:); y1 = y1(:); x2 = x2(:);y2 = y2(:);

% Compute number of line segments in each curve and some differences we'll % need later.

n1 = length(x1) - 1; n2 = length(x2) - 1; xy1 = [x1 y1]; xy2 = [x2 y2]; dxy1 = diff(xy1);dxy2 = diff(xy2); % Determine the combinations of i and j where the rectangle enclosing the

% i'th line segment of curve 1 overlaps with the rectangle enclosing the % j'th line segment of curve 2.

[i,j] = find(repmat(min(x1(1:end-1),x1(2:end)),1,n2) <= ...repmat(max(x2(1:end-1),x2(2:end)).',n1,1) & ...repmat(max(x1(1:end-1),x1(2:end)),1,n2) >= ...repmat(min(x2(1:end-1),x2(2:end)).',n1,1) & ...repmat(min(y1(1:end-1),y1(2:end)),1,n2) <= ...repmat(max(y2(1:end-1),y2(2:end)).',n1,1) & ...repmat(max(y1(1:end-1),y1(2:end)),1,n2) >= ...repmat(min(y2(1:end-1),y2(2:end)).',n1,1));

% Find segments pairs which have at least one vertex = NaN and remove them.

```
% This line is a fast way of finding such segment pairs. We take
```

% advantage of the fact that NaNs propagate through calculations, in

% particular subtraction (in the calculation of dxy1 and dxy2, which we % need anyway) and addition.

remove = isnan(sum(dxy1(i,:) + dxy2(j,:),2));i(remove) = [];

j(remove) = [];

% Initialize matrices. We'll put the T's and B's in matrices and use them % one column at a time. AA is a 3-D extension of A where we'll use one % plane at a time.

n = length(i); T = zeros(4,n); AA = zeros(4,4,n); AA([1 2],3,:) = -1; AA([3 4],4,:) = -1; AA([1 3],1,:) = dxy1(i,:).'; AA([2 4],2,:) = dxy2(j,:).';B = -[x1(i) x2(j) y1(i) y2(j)].';

% Loop through possibilities. Trap singularity warning and then use
% lastwarn to see if that plane of AA is near singular. Process any such
% segment pairs to determine if they are colinear (overlap) or merely
% parallel. That test consists of checking to see if one of the endpoints
% of the curve 2 segment lies on the curve 1 segment. This is done by
% checking the cross product

% (x1(2),y1(2)) - (x1(1),y1(1)) x (x2(2),y2(2)) - (x1(1),y1(1)). %
% If this is close to zero then the segments overlap. for k = 1:n [L,U] = lu(AA(:,:,k)); T(:,k) = U\(L\B(:,k)); % Find where t1 and t2 are between 0 and 1 and return the corresponding % x0 and y0 values. in\_range = T(1,:) >= 0 & T(2,:) >= 0 & T(1,:) < 1 & T(2,:) < 1;x0 =  $T(3,in_range).';$ y0 =  $T(4,in_range).';$ end

end