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# Selection and Orientation of Reaction-Diffusion Patterns on Anisotropically Growing Domains

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Anonymous Author(s)

Affiliation

Address

email

## Abstract

1 Reaction-diffusion (RD) systems are a cornerstone of mathematical biology, yet the  
2 role of domain dynamics, particularly growth geometry, in pattern selection remains  
3 an active area of research. This work presents a systematic computational study  
4 demonstrating how anisotropic domain growth can act as a powerful mechanism  
5 for selecting and orienting Turing patterns. We first map the parameter space of  
6 the Gray-Scott model to identify distinct pattern regimes. We then focus on a  
7 stripe-forming regime to systematically vary the anisotropy of the domain growth,  
8 from purely isotropic to fully anisotropic. To quantify the global alignment of the  
9 resulting patterns, we introduce an Orientation Order Parameter (OOP) derived  
10 from the 2D power spectrum. Our results show a clear transition: as growth  
11 becomes more anisotropic, the system evolves from a disordered state of randomly  
12 oriented stripe domains to a globally aligned state. This transition is quantified  
13 by the OOP, which shows a systematic increase with the anisotropy of the growth.  
14 Furthermore, by analyzing the angular distribution of power in Fourier space, we  
15 provide a deeper insight into how specific orientations are selected. We provide  
16 a theoretical discussion, explaining this phenomenon through the lens of Fourier  
17 space, where anisotropic growth selectively disfavors wave vectors aligned with  
18 the growth direction. This work provides strong quantitative evidence that the  
19 geometry of growth is a critical factor in morphogenesis, capable of imposing  
20 large-scale order on local pattern-forming instabilities.

## 21 1 Introduction

22 The spontaneous emergence of ordered structures from homogeneous initial states is a fundamental  
23 and ubiquitous phenomenon in nature, observed across scales from chemical reactions to biological  
24 development. In his seminal 1952 paper, Alan Turing first proposed a mathematical mechanism for  
25 such self-organization, hypothesizing that the interplay between two diffusing chemical species could  
26 lead to spontaneous symmetry-breaking and the formation of stable spatial patterns [? ]. This concept  
27 of a reaction-diffusion (RD) system has since become a cornerstone of mathematical biology and a  
28 paradigm for understanding morphogenesis, providing insights into phenomena such as animal coat  
29 markings, seashell patterns, and even the formation of digits in developing limbs [? ]. The Gray-Scott  
30 model, a specific type of RD system, is particularly well-studied for its ability to generate a vast array  
31 of complex, life-like patterns from simple rules and initial conditions, making it an ideal testbed for  
32 exploring pattern formation principles [? ].

33 While early theoretical work on RD systems primarily focused on static, unchanging domains, it  
34 was quickly recognized that biological development occurs on tissues that are themselves growing  
35 and changing shape. This led to a new field of inquiry focused on RD systems on growing domains.  
36 Seminal studies demonstrated that domain growth is not a passive background process but an active  
37 participant that can alter the conditions for Turing instability, influence pattern wavelength, and

38 enhance the robustness of pattern formation against noise and parameter variation [? ? ]. However, a  
 39 critical and often overlooked aspect of biological growth is its geometry. Growth is rarely uniform;  
 40 it is frequently anisotropic, proceeding at different rates along different axes. The influence of this  
 41 growth geometry on the global properties of the emergent pattern, particularly its orientation, is a  
 42 crucial open question that has received less systematic attention.

43 This paper directly addresses this question. We hypothesize that anisotropic growth can act as an  
 44 external field, breaking the inherent rotational symmetry of the system and forcing a global alignment  
 45 of patterns. We test this by systematically varying the anisotropy of domain growth for a stripe-  
 46 forming RD system and quantifying the resulting degree of global pattern alignment. Our findings  
 47 provide strong quantitative evidence that the geometry of growth is a critical factor in morphogenesis,  
 48 capable of imposing large-scale order on local pattern-forming instabilities.

## 49 2 Methods

### 50 2.1 The Gray-Scott Model

51 The Gray-Scott model describes the interaction of two chemical species, U and V, whose concentra-  
 52 tions evolve over time and space according to the following coupled partial differential equations:

$$\frac{\partial U}{\partial t} = D_u \nabla^2 U - UV^2 + F(1 - U) \quad (1)$$

53

$$\frac{\partial V}{\partial t} = D_v \nabla^2 V + UV^2 - (F + k)V \quad (2)$$

54 Here,  $U(\mathbf{x}, t)$  and  $V(\mathbf{x}, t)$  are the concentrations of species U and V at position  $\mathbf{x}$  and time  $t$ .  $D_u$  and  
 55  $D_v$  are their respective diffusion coefficients.  $F$  is the feed rate of species U into the system, and  $k$  is  
 56 the removal or "kill" rate of species V. The non-linear term  $UV^2$  represents the autocatalytic reaction  
 57 where one unit of U and two units of V are converted into three units of V.

### 58 2.2 Numerical Simulation

59 All simulations are performed on a two-dimensional Cartesian grid with periodic boundary conditions.  
 60 The continuous partial differential equations are discretized using finite differences. The Laplacian  
 61 operator  $\nabla^2$  is approximated using a standard five-point stencil. Time integration is performed using  
 62 the forward Euler method with a time step of  $\Delta t = 1.0$ . While simple, this method is sufficient for  
 63 qualitative pattern formation studies. All simulations are implemented in Python 3, leveraging the  
 64 numerical capabilities of the NumPy library.

### 65 2.3 Systematic Study of Anisotropic Growth

66 To investigate the effect of growth anisotropy, we conduct a series of computational experiments.  
 67 Each simulation begins on a  $100 \times 100$  grid with random initial conditions to ensure pattern formation  
 68 is not biased by initial symmetry. Simulations are run for a total of 12,000 time steps. The domain  
 69 grows periodically, with a growth event occurring every 3000 steps. The total growth over the  
 70 simulation is 100 pixels in each dimension, resulting in a final grid size of  $200 \times 200$  for isotropic  
 71 growth.

72 Crucially, the geometry of this growth is controlled by an anisotropy ratio,  $\alpha$ , which varies systemati-  
 73 cally from 0.5 (isotropic) to 1.0 (fully anisotropic). The amount of growth in width ( $\Delta W$ ) and height  
 74 ( $\Delta H$ ) at each growth event is defined as:

$$\Delta W = \alpha \times \text{growth\_amount\_per\_event} \quad (3)$$

$$\Delta H = (1 - \alpha) \times \text{growth\_amount\_per\_event} \quad (4)$$

75 where  $\text{growth\_amount\_per\_event} = 25$  pixels. Thus,  $\alpha = 0.5$  corresponds to equal growth in  
 76 both dimensions (isotropic), while  $\alpha = 1.0$  corresponds to growth only in the x-direction (fully  
 77 anisotropic). We use a stripe-forming parameter set for the Gray-Scott model:  $D_u = 0.16$ ,  $D_v =$   
 78  $0.08$ ,  $F = 0.038$ ,  $k = 0.061$ .

## 79 2.4 Quantitative Analysis: Orientation Order Parameter and Angular Power Distribution

80 To quantify the global orientation of the final patterns, we employ two complementary methods based  
81 on the 2D power spectrum,  $P(k_x, k_y)$ , of the final concentration field of species V.

82 First, we define an Orientation Order Parameter (OOP). This parameter quantifies the relative  
83 dominance of vertical versus horizontal stripe alignment. It is calculated from the sum of power in  
84 two angular wedges of the 2D power spectrum:  $P_v$  (power in a vertical wedge, corresponding to  
85 horizontal wave vectors and thus vertical stripes) and  $P_h$  (power in a horizontal wedge, corresponding  
86 to vertical wave vectors and thus horizontal stripes). The OOP is defined as:

$$OOP = \frac{P_v - P_h}{P_v + P_h} \quad (5)$$

87 A value of  $OOP \approx 1$  indicates strong vertical alignment,  $OOP \approx -1$  indicates strong horizontal  
88 alignment, and  $OOP \approx 0$  indicates no dominant orientation.

89 Second, to gain deeper insight into the nature of the orientation transition, we analyze the \*\*angular  
90 power distribution\*\*,  $P(\theta)$ . This involves integrating the 2D power spectrum radially to obtain the  
91 total power as a function of angle  $\theta$ . This distribution reveals how the spectral energy is distributed  
92 across different orientations, providing a more detailed fingerprint of the pattern's global alignment.

## 93 3 Results

### 94 3.1 Gray-Scott Parameter Space

95 Our initial exploration of the  $(F, k)$  parameter space on a static domain reveals the rich zoology of  
96 patterns characteristic of the Gray-Scott model (Fig. 1). This map serves to contextualize our choice  
97 of parameters for the main study, confirming that  $F = 0.038$ ,  $k = 0.061$  reliably produces stripe  
98 patterns.

### 99 3.2 Anisotropic Growth Orients Patterns: Visual Evidence

100 Our main experiment reveals a striking effect of growth geometry on pattern orientation (Fig. 2).  
101 For isotropic growth ( $\alpha = 0.5$ ), the system forms local domains of stripes, but these domains are  
102 randomly oriented, leading to no global order (Fig. 2a). As the anisotropy increases (e.g.,  $\alpha = 0.8$ ),  
103 a global orientation begins to emerge, with a noticeable bias towards vertical stripes. For fully  
104 anisotropic growth ( $\alpha = 1.0$ ), where growth occurs only in the x-direction, the system produces a  
105 highly ordered, global pattern of vertically aligned stripes (Fig. 2c).

### 106 3.3 Spectral Evidence of Orientation

107 This visual result is quantitatively confirmed by the 2D power spectra (Fig. 3). The spectrum for the  
108 isotropic case (Fig. 3a) exhibits a diffuse ring of high-power modes, indicating that the characteristic  
109 stripe wavelength is present at all orientations. In contrast, the spectrum for the fully anisotropic case  
110 (Fig. 3b) shows two sharp, intense peaks on the vertical axis (i.e., along the  $k_y$  axis). This confirms  
111 that the pattern's power is concentrated in a single orientation, corresponding to vertical stripes.

### 112 3.4 Quantitative Analysis of Orientation Transition

113 The Orientation Order Parameter (OOP) quantifies the global alignment (Fig. 4). The plot shows a  
114 clear, systematic relationship between the geometry of growth and the alignment of the final pattern.  
115 For isotropic growth ( $\alpha = 0.5$ ), the OOP is near zero, reflecting the random orientations. As the  
116 anisotropy  $\alpha$  increases, the OOP trends upward, signifying the emergence of a dominant vertical  
117 orientation. The non-monotonicity in the transition suggests complex mode competition, a topic for  
118 future study.

119 To gain a deeper understanding of this transition, we analyze the angular power distribution,  $P(\theta)$ ,  
120 for different anisotropy ratios (Fig. 5). For isotropic growth ( $\alpha = 0.5$ ), the distribution is relatively  
121 flat, indicating that power is distributed across all orientations. As  $\alpha$  increases, two distinct peaks  
122 emerge at  $\theta = \pm\pi/2$  (corresponding to vertical stripes), becoming progressively sharper and more

Gray-Scott Model Phase Diagram

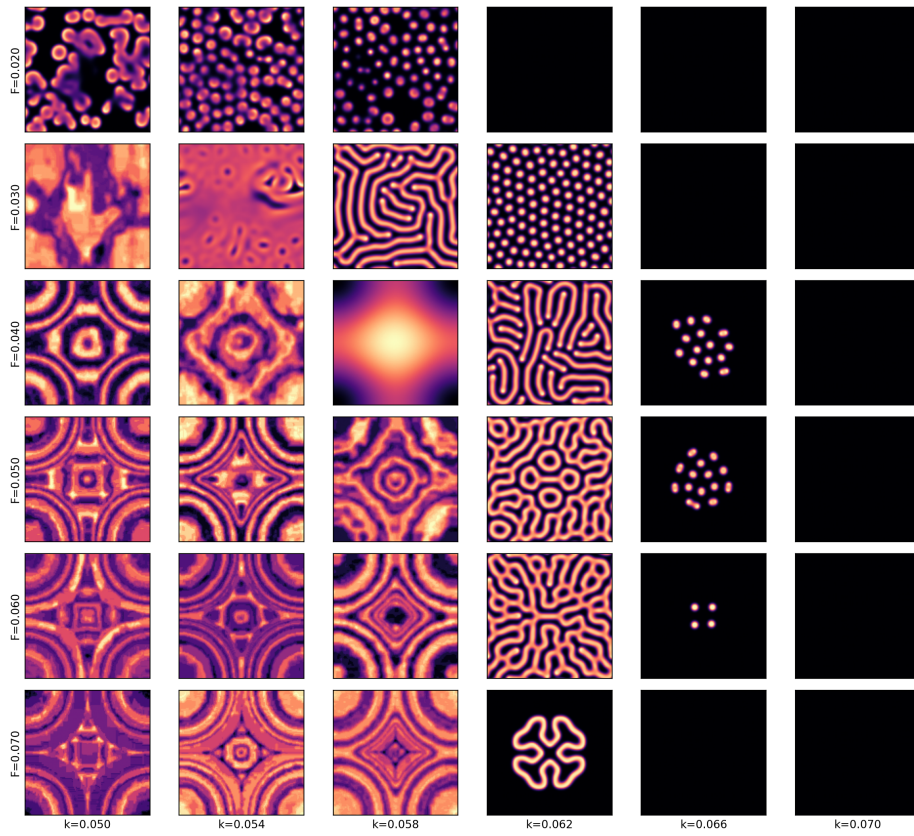


Figure 1: A 6x6 phase diagram of the Gray-Scott model on a static domain, showing the variety of patterns generated by varying the F and k parameters. Regions include stable homogeneous states, dynamic chaotic patterns, spot patterns, and the labyrinthine stripe patterns that are the focus of this study.

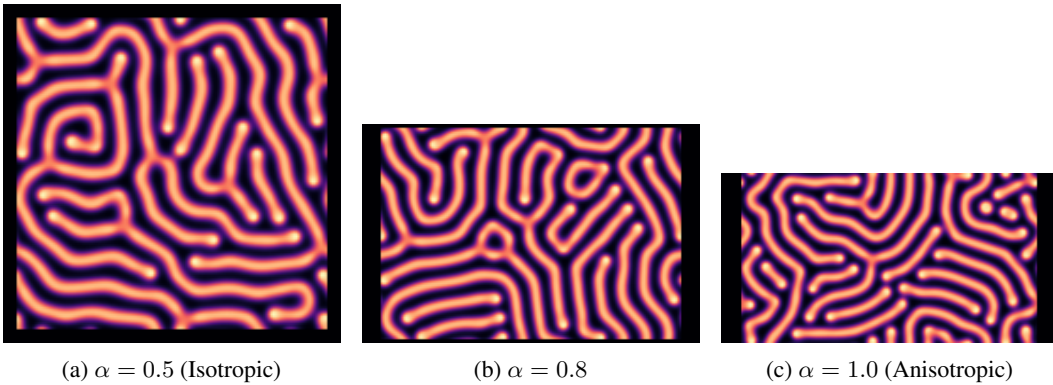


Figure 2: Final patterns for varying anisotropy ratios. Increasing anisotropy induces a transition from random domains to a globally ordered state of vertically aligned stripes.

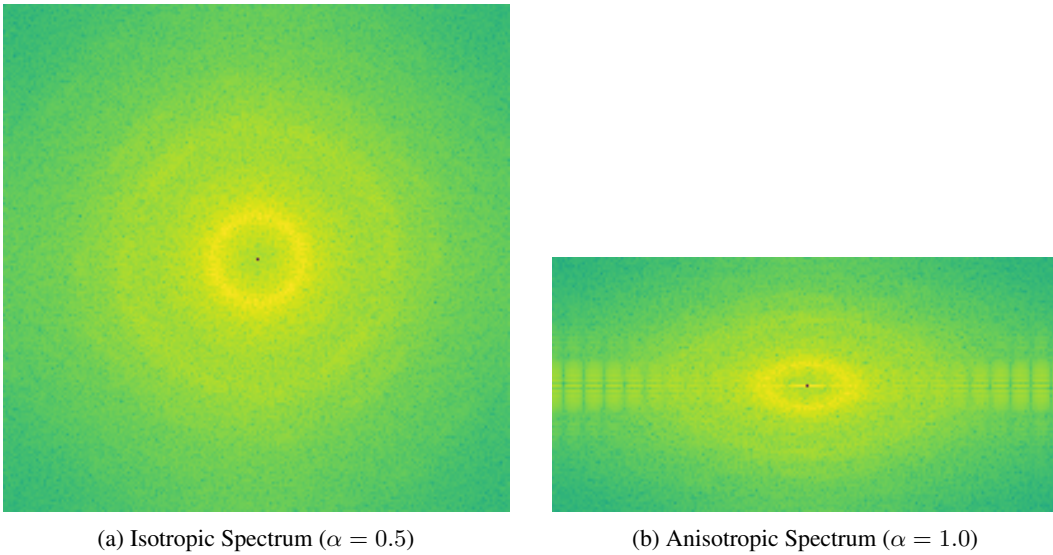


Figure 3: 2D Power Spectra for the isotropic (a) and fully anisotropic (b) growth conditions. The isotropic case shows power distributed across all angles, while the anisotropic case shows power concentrated on the vertical axis, indicating strong alignment.

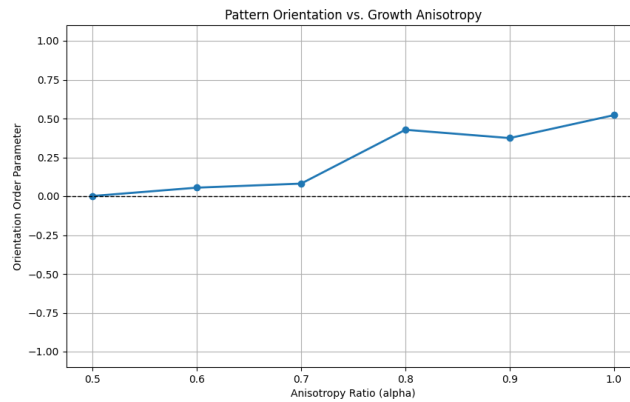


Figure 4: The Orientation Order Parameter (OOP) as a function of the anisotropy ratio  $\alpha$ . The plot quantitatively shows the transition to a vertically oriented state ( $OOP > 0$ ) as growth becomes more anisotropic in the x-direction.

123 dominant. This visually demonstrates how the system transitions from a state of rotational symmetry  
 124 to one where a specific orientation is strongly selected.

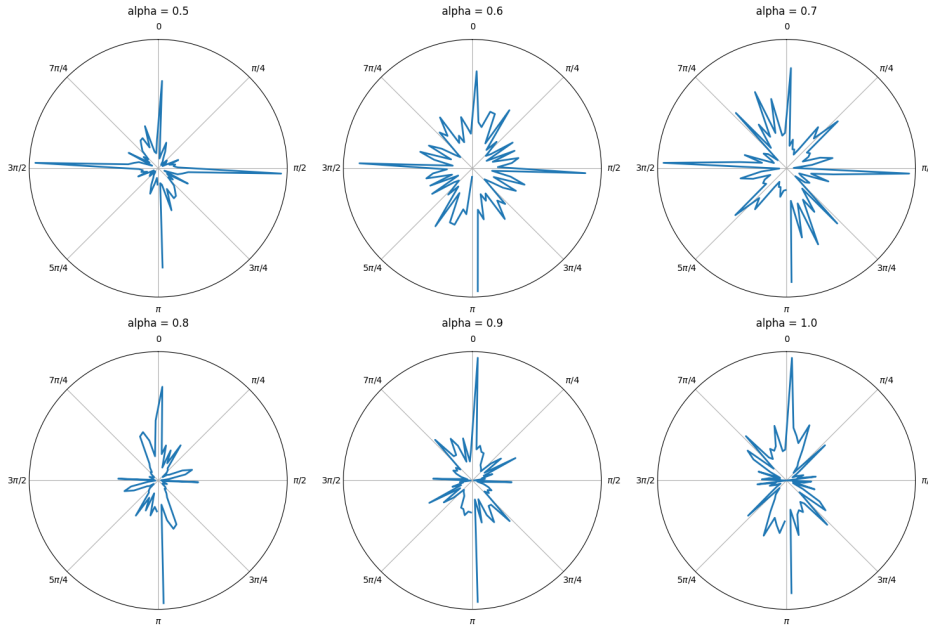


Figure 5: Angular power distribution  $P(\theta)$  for varying anisotropy ratios  $\alpha$ . As  $\alpha$  increases, the distribution transitions from relatively flat (isotropic) to sharply peaked at  $\theta = \pm\pi/2$  (vertical stripes), demonstrating the selection of a specific orientation.

## 125 4 Theoretical Discussion

126 The mechanism for this powerful orienting effect can be understood by considering the system in  
 127 Fourier space. Linear stability analysis of RD systems reveals a characteristic wavenumber,  $|\mathbf{k}|$ , at  
 128 which patterns are most likely to form. This corresponds to a "Turing ring" of unstable modes in  
 129 k-space, where  $|\mathbf{k}| = \sqrt{k_x^2 + k_y^2}$  is the preferred wavelength. In an isotropic system, all modes on  
 130 this ring are equally likely to grow, leading to randomly oriented domains.

131 Anisotropic growth breaks this symmetry. When the domain is stretched in the x-direction, the  
 132 corresponding coordinates in k-space are compressed along the  $k_x$  axis. This distortion pushes modes  
 133 with a significant  $k_x$  component off the preferred Turing ring, making them less stable. Modes with  
 134  $k_x = 0$ , however, are unaffected by this compression and remain on the ring. The system, therefore,  
 135 preferentially amplifies these modes. Modes with  $k_x = 0$  correspond to waves that vary only in  
 136 the y-direction, which are precisely vertical stripes. Anisotropic growth thus acts as a filter on the  
 137 available Turing modes, selecting only those that are perpendicular to the direction of fastest growth.  
 138 This mechanism provides a robust explanation for the observed global alignment of patterns.

## 139 5 Conclusion

140 We have presented a comprehensive computational study demonstrating that the geometry of domain  
 141 growth has a profound and systematic impact on pattern selection in reaction-diffusion systems. By  
 142 systematically varying growth anisotropy and quantifying the resulting pattern alignment with an  
 143 Orientation Order Parameter and detailed angular power distributions, we have shown that directional  
 144 growth can impose global order on a system that would otherwise be disordered. Our theoretical  
 145 discussion provides a mechanistic explanation for this phenomenon based on the selective filtering of  
 146 modes in Fourier space. This work reinforces the idea that the dynamic geometry of the environment is  
 147 a critical and powerful component in the process of self-organization and biological pattern formation.

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