

## **ABSTRACT**

### **A Beefy Frangi Filter for Noisy Vascular Segmentation and Network Connection in PCSVN**

**By**

**Lucas Wukmer**

**May 2018**

Recent statistical analysis of placental features has suggested the usefulness of studying key features of the placental chorionic surface vascular network (PCSVN) as a measure of overall neonatal health. A recent study has suggested that reliable reporting of these features may be useful in identifying risks of certain neurodevelopmental disorders at birth. The necessary features can be extracted from an accurate tracing of the surface vascular network, but such tracings must still be done manually, with significant user intervention. Automating this procedure would not only allow more data acquisition to study the potential effects of placental health on later conditions, but may ideally serve as a real-time diagnostic for neonatal risk factors as well.

Much work has been to develop reliable vascular extraction methods for well-known image domains (such as retinal MRA images) using Hessian-based filters, namely the (multiscale) Frangi filter. It is desirable to extend these arguments to placental images, but this approach is greatly hindered by the inherent irregularity of the placental surface as a whole, which introduces significant noise into the image domain. A recent attempt was made to apply an additional local curvilinear filter to the Frangi result in an effort to remove some noise from the final extraction.

Here we propose an alternate extraction method. First, we use arguments from Frangis original paper to provide a proper selection of parameters for our particular image domain. Using the same arguments from differential geometry that gave rise to the Frangi filter, we calculate the leading principal direction (eigenvector of the Hessian) to indicate the directionality of curvilinear

features at a particular scale. We are then able to apply an appropriately-oriented morphological filter to our Frangi targets at select scales to remove noise. This approach differs significantly from previous efforts in that morphological filtering will take place at each scale space, rather than being performed one time following multiscale synthesis. Noise removal performed in this way is expected to aide in coherent interpretation of targets that should appear in a connected network.

Finally, we discuss an important advancement in implementation—scale space conversion for differentiation (i.e. gaussian blur) via Fast Fourier Transform (FFT) rather than a more traditional convolution with a gaussian kernel, which offers a significant speedup. This thesis will also contain a general, in depth summary of both multiscale Hessian filters and scale-space theory.

We demonstrate the effectiveness of our improved vascular extraction technique on several of the following image domains: a private database of barium-injected samples provided by University of Rochester, uninjected/raw placental samples from Placental Analytics LLC, a collection of simulated images, the DRIVE and STARE databases of retinal MRAs, and a new collection of computer-generated images with significant curvilinear content.

Time permitting, this research will be extended to include a method of network connection, so that a logically connected vascular network is realized (i.e. network completion).

# **A Beefy Frangi Filter for Noisy Vascular Segmentation and Network Connection in PCSVN**

## **A THESIS**

Presented to the Department of Department of Mathematics and Statistics

California State University, Long Beach

In Partial Fulfillment

of the Requirements for the Degree

Master of Science in Applied Mathematics

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B.S., 2013, University of California, Los Angeles

May 2018

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HAVE APPROVED THIS THESIS

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Acknowledgments go here.

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# **CHAPTER 1**

## **INTRODUCTION**

### **The Applied Problem**

Reference Nen's paper and latest autism risk paper.

### **Context in Image Processing**

- brief background of math image processing methods
- what's been tried in this applied problem
  - nen [1]
  - catalina's paper
  - kara's paper
  - other domains

### **Research Goals**

Segue from previous paragraph, talk about strengths and weaknesses of other methods and what this research aims to accomplish. Include 'research questions' that could allow a reader to answer the question "will this research work for my problem?". "Elevator pitch" maybe goes here.

### **Roadmap**

Outline of the thesis ("firstly" bullshit)

## CHAPTER 2

### MATHEMATICAL METHODS

#### Overview of Differential Geometry in Image Processing

##### Basics, Definitions

**Definition 2.1.1.** *For theoretical purposes, we may view any 2D grayscale image as a continuous function  $L : \mathbb{R}^2 \rightarrow \mathbb{R}$  with  $L \in C^2(\mathbb{R}^2)$ .*

**Definition 2.1.2.** *In the context of differential geometry, we wish to refer to its graph  $f : \mathbb{R}^2 \rightarrow \mathbb{R}^3$  by  $(u, v) \mapsto (u, v, L(u, v))$ .*

**Definition 2.1.3.** *In situations where we wish to discuss a discrete image, we may refer to  $L_0 \in \mathbb{R}^{m \times n}$ . That is,  $L_0$  is a matrix corresponding to the  $m$ -by- $n$  digital grayscale image.*

Viewing the surface in  $\mathbb{R}^3$ , we define the Hessian  $\mathcal{H}$  of the surface  $L$  at a point  $(x, y)$  on the surface as the matrix of its second partial derivatives:

$$\mathcal{H}(x, y) = \begin{bmatrix} L_{xx}(x, y) & L_{xy}(x, y) \\ L_{yx}(x, y) & L_{yy}(x, y) \end{bmatrix} \quad (2.1)$$

At any point  $(x, y)$  we denote the two eigenpairs of  $\mathcal{H}(x, y)$  as

$$\mathcal{H}u_i = \kappa_i u_i, \quad i = 1, 2 \quad (2.2)$$

where  $\kappa_i$  and  $u_i$  are known as the *principal curvatures* and *principal directions* of  $L(x, y)$ , respectively, and we label such that  $|\kappa_2| \geq |\kappa_1|$ . Notably,  $\mathcal{H}(x, y)$  is a real, symmetric matrix (since  $L_{xy} = L_{yx}$  and  $L$  is a real function) and thus its eigenvalues are real and its eigenvectors are orthonormal to each other, as given by following lemma:

**Lemma 2.1.1** (Principal Axis Theorem?). *Let  $A$  be a real, symmetric matrix. The eigenvalues of  $A$  are real and its eigenvectors are orthonormal to each other.*

*Proof.* Let  $x \neq 0$  so that  $Ax = \lambda x$ . Then

$$\begin{aligned}\|Ax\|_2^2 &= \langle Ax, Ax \rangle = (Ax)^* Ax \\ &= x^* A^* Ax = x^* A^T Ax = x^* A Ax \\ &= x^* A \lambda x = \lambda x^* Ax \\ &= \lambda x^* \lambda x = \lambda^2 x^* x = \lambda^2 \|x\|_2^2\end{aligned}$$

Upon rearrangement, we have  $\lambda^2 = \frac{\|Ax\|_2^2}{\|x\|_2^2} \geq 0 \implies \lambda$  is real.

To prove that a set of orthonormalizable eigenvectors exists, let  $A$  be real, symmetric as above and consider the eigenpairs  $Av_1 = \lambda_1 v_1$ ,  $Av_2 = \lambda_2 v_2$  with  $v_1, v_2 \neq 0$ .<sup>1</sup>

In the case that  $\lambda_1 \neq \lambda_2$ , we have

$$\begin{aligned}(\lambda_1 - \lambda_2)v_1^T v_2 &= \lambda_1 v_1^T v_2 - \lambda_2 v_1^T v_2 \\ &= (\lambda_1 v_1)^T v_2 - v_1^T (\lambda_2 v_2) \\ &= (Av_1)^T v_2 - v_1^T (Av_2) \\ &= v_1^T A^T v_2 - v_1^T Av_2 \\ &= v_1^T Av_2 - v_1^T Av_2 = 0\end{aligned}$$

Since  $\lambda_1 \neq \lambda_2$ , we conclude that  $v_1^T v_2 = 0$ .

In the case that  $\lambda_1 = \lambda_2 =: \lambda$ , we can define (as in Gram-Schmidt orthogonalization)

---

<sup>1</sup>To simplify notation, we simplify our argument to consider two explicit eigenvectors only, since we're only concerned with the  $2 \times 2$  matrix  $\mathcal{H}$  anyway.

$u = v_2 - \frac{v_1^T v_2}{v_1^T v_1} v_1$ . This is an eigenvector for  $\lambda = \lambda_2$ , as

$$\begin{aligned} Au &= A \left( v_2 - \frac{v_1^T v_2}{v_1^T v_1} v_1 \right) \\ &= Av_2 - \frac{v_1^T v_2}{v_1^T v_1} Av_1 \\ &= \lambda v_2 - \frac{v_1^T v_2}{v_1^T v_1} \lambda v_1 \\ &= \lambda \left( v_2 - \frac{v_1^T v_2}{v_1^T v_1} v_1 \right) = \lambda u \end{aligned}$$

and is perpendicular to  $v_1$ , since

$$\begin{aligned} v_1^T u &= v_1^T \left( v_2 - \frac{v_1^T v_2}{v_1^T v_1} v_1 \right) \\ &= v_1^T v_2 - \left( \frac{v_1^T v_2}{v_1^T v_1} \right) v_1^T v_1 \\ &= v_1^T v_2 - v_1^T v_2 (1) = 0. \end{aligned}$$

□

Thus we see that the two principal directions form an orthonormal frame at each point  $(x, y)$  within the continuous image  $L(x, y)$ .

✂The following is an **unverified claim** (which might be useful for later): The frame varies continuously along paths in  $\mathbb{R}^2$  except at points where  $\mathcal{H}(x, y)$  is singular. To make this explicit:

**Theorem 2.1.2** (Continuity of the leading principal direction). *Let  $\theta : I := [0, 1] \rightarrow \mathbb{R}^2$  be a parametrized regular curve in  $\mathbb{R}^2$  and  $H_\theta := \mathcal{H}_f \circ \theta(t)$  be the matrix-valued function (where  $\mathcal{H}_f$  is the  $2 \times 2$  Hessian of the smooth surface  $f$ ) Let  $U : I \rightarrow \mathbb{R}^2$  be the implicitly-defined vector valued function s.t.  $U(t)$  is the leading eigenvector of  $H_\theta$  (and therefore the leading principal direction of  $f$ ). That is,*

$$H_\theta U(t) = \lambda U(t) \quad \text{with} \quad \lambda = \rho(H_\theta) \quad (2.3)$$

*In other words,  $|\lambda| \geq |\tilde{\lambda}|$  for any  $\tilde{\lambda} : H_\theta u = \tilde{\lambda} u$  for some  $u \neq 0$ .*

*Then,  $U(t)$  is continuous in  $t$  whenever  $H_f(t)$  is non-singular. Note: Maybe fix this so that the path avoids any nonsingular points?  $U(t)$  isn't even well-defined at such points anyway.*

*Proof.* First, we show that  $U(t)$  is a well-defined function at all points  $t$  where  $H_f(t)$  is non-singular. □

✂TODO

---

## Eigenvectors of the Hessian are principal curvature directions

✂TO-DO **REWRITE THIS AS A PARAGRAPH AND/OR INTERSPERSE  
THROUGHOUT THE SECTION**

Formally, within the context of differential geometry, we should show a few things:

- definition of curvature of a surface (how it relates to curvature of a regular curve) and showing that it's invariant of which curve is taken—that is, it only depends on a tangent vector to the surface.
- normal curvature is given by the second fundamental form  $\mathbf{II}(X, X) = \langle LX, X \rangle$  where  $L$  is the Weingarten map.
- $X$  is an extremal value of  $\mathbf{II}(X, X)$  subject to  $\mathbf{I}(X, X) = 1$  iff  $X$  is an eigenvector of  $L$ .
- In the case of a surface  $f(u, v) = (u, v, h(u, v))$  (i.e. graph of a 2D function, which is the only situation we care about in image processing), the Weingarten map is exactly the Hessian matrix.

## Preliminaries of Differential Geometry / Notational Dump

Given an open subset  $U \subset \mathbb{R}^2$  and a twice differentiable function  $h : U \rightarrow \mathbb{R}$ . then we define its *graph*  $f$  as

$$f : U \rightarrow \mathbb{R}^3 \quad \text{by} \quad f(u_1, u_2) = (u_1, u_2, h(u_1, u_2)) \quad , \quad u = (u_1, u_2) \in U$$

For any point  $u \in U$ , we associate a  $p \in f[U]$ , i.e.  $p = f(u)$ .

We define the tangent plane of  $f$  at point  $p$  as the map

$$T_u f := Df|_u(T_u U) \subset T_{f(u)} \mathbb{R}^3$$

where  $Df|_x$  is the differential map of  $f$  at point  $x$  given by

$$Df|_x : U \rightarrow \mathbb{R}^3 \quad \text{by} \quad v \mapsto J_f(x) \cdot v$$

where  $J_f(x)$  is the Jacobian of  $f$  evaluated at point  $x$ , i.e. the matrix

$$J_f(x) = \left[ \frac{\partial f_i}{\partial u_j} \Big|_x \right]_{i,j}$$

We shall denote a tangent vector  $X \in T_u f$  at point  $p$ . It is easily shown that we may expand any such vector  $X$  in terms of the basis  $\left\{ \frac{\partial f}{\partial u_i} \right\}_{i=1,2}$ ; that is,  $\text{span} \left\{ \frac{\partial f}{\partial u_1}, \frac{\partial f}{\partial u_2} \right\} = T_u f$ .

Given a closed interval  $I \subset \mathbb{R}$ , we can define a regular curve on the surface  $c : I \rightarrow \mathbb{R}^3$  such that  $\text{image}(c) \subset \text{image}(f)$ . In other words, we can (for this particular curve) define an intermediary parametrization  $\theta_c$  for this curve so that  $c = f \circ \theta_c$  i.e.

$$\theta_c : I \rightarrow U \text{ by } \theta(t) = (\theta_1(t), \theta_2(t))$$

and  $c(t) = f(\theta(t))$ .

We also shall define at a point  $p = f(u)$  the Gauss map

$$\mathbf{v} : U \rightarrow S^2 \quad \text{by} \quad \mathbf{v}(u_1, u_2) := \frac{\frac{\partial f}{\partial u_1} \times \frac{\partial f}{\partial u_2}}{\left\| \frac{\partial f}{\partial u_1} \times \frac{\partial f}{\partial u_2} \right\|}$$

with each partial above understood to be evaluated at the input  $u \in U$ .

It is clear that  $\mathbf{v} \perp \frac{\partial f}{\partial u_i}$  each  $i = 1, 2$ , and also that  $\text{span} \left\{ \frac{\partial \mathbf{v}}{\partial u_1}, \frac{\partial \mathbf{v}}{\partial u_2} \right\} = T_u f$  as well.

### Defining normal curvature of a surface

In the context of a regular arc-length parametrized curve  $c : I \rightarrow \mathbb{R}^3$  parametrized along some closed interval  $I \in \mathbb{R}$  (that is, a differentiable, one-to-one curve where  $c'(s) = 1 \quad \forall s \in I$ ),

curvature at a point  $s \in I$  is defined simply as the magnitude of the curve's acceleration:

$$\kappa(s) := \|c''(s)\|.$$

To extend the notion of curvature of a surface  $f$ , we can consider the curvature of such a curve embedded within the surface: that is,  $c[I] = f[\theta_c[I]]$ . Considering a point  $p \in I$  and its associated point  $u = \theta_c(p)$ , we wish to compare the curvatures of all curves at the point with a shared velocity. We now present a main result that provides a notion of curvature of a surface.

✂*TODO fix so this is clearer and less bogged down by  $u \leftrightarrow p$  conversion so you can more easily tell what all curves have in common*

**Theorem 2.2.1** (Theorem of Meusnier). *Given a point  $u \in U$  and a tangent direction  $X \in T_u\mathbb{R}^3$ , any curve on the surface  $c : I \rightarrow \text{image}(f)$  with  $p \in I : \theta_c(p) = u$  where  $c'(p) = X$  will have the same curvature.*

*Proof.* Considering any such curve where  $\frac{\partial c}{\partial t}(p) = X$  where  $X \in T_u\mathbb{R}^3$  is a normalized vector tangent to the surface at the point  $u$ , we wish to decompose its acceleration along the orthogonal vectors  $X$  and the Gauss map  $\mathbf{v} := \mathbf{v}(u_1, u_2) = \frac{\frac{\partial f}{\partial u_1} \times \frac{\partial f}{\partial u_2}}{\|\frac{\partial f}{\partial u_1} \times \frac{\partial f}{\partial u_2}\|}$ . (Note that  $X$  and  $\mathbf{v}$  are indeed orthogonal, as both  $\frac{\partial f}{\partial u_i} \in T_u\mathbb{R}^3$ ,  $i = 1, 2$ .) We then have (at this fixed point  $u = \theta_c(p)$ )

$$c'' = \langle c'', X \rangle X + \langle c'', \mathbf{v} \rangle \mathbf{v} \quad (2.4)$$

.

The first term is zero, since for a regular curve

$$\langle c'', X \rangle = \langle c'', c' \rangle = 0$$

since either  $c'' \perp c'$  or  $\|c''\| = 0$  itself (which is generally true for a regular curve in  $\mathbb{R}^3$ )



Using chain rule, we can rewrite the second coefficient of (2.4) as

$$\langle c'', \mathbf{v} \rangle = \frac{\partial}{\partial t} [\langle c', \mathbf{v} \rangle] - \langle c', \frac{\partial \mathbf{v}}{\partial t} \rangle \quad (2.5)$$

$$= \frac{\partial}{\partial t} [\langle X, \mathbf{v} \rangle] - \langle c', \frac{\partial \mathbf{v}}{\partial t} \rangle \quad (2.6)$$

$$= 0 - \langle X, \frac{\partial \mathbf{v}}{\partial t} \rangle \quad (2.7)$$

Thus, we can express the curvature at this point on our selected curve as

$$\|c''\| = \|\langle c'', X \rangle X + \langle c'', \mathbf{v} \rangle \mathbf{v}\| = \|0 + \langle c'', \mathbf{v} \rangle \mathbf{v}\| \quad (2.8)$$

$$= -\langle X, \frac{\partial \mathbf{v}}{\partial t} \rangle \|\mathbf{v}\| \quad (2.9)$$

$$= -\langle X, \frac{\partial \mathbf{v}}{\partial t} \rangle \quad (2.10)$$

$$= \langle X, -\frac{\partial \mathbf{v}}{\partial t} \rangle \quad (2.11)$$

We may compute  $-\frac{\partial \mathbf{v}}{\partial t}$  via chain rule:

$$-\frac{d\mathbf{v}}{dt} = -\frac{d}{dt} [\mathbf{v}(\theta_1(t), \theta_2(t))] \quad (2.12)$$

$$= \theta'_1(s) \left( -\frac{\partial \mathbf{v}}{\partial u_1} \right) + \theta'_2(s) \left( -\frac{\partial \mathbf{v}}{\partial u_2} \right) \quad (2.13)$$

Using this, we can rewrite the curvature for our curve as

$$\|c''\| = \|\langle c'', X \rangle X + \langle c'', \mathbf{v} \rangle \mathbf{v}\| = \|0 + \langle c'', \mathbf{v} \rangle \mathbf{v}\| \quad (2.14)$$

$$= -\langle X, \frac{\partial \mathbf{v}}{\partial t} \rangle \|\mathbf{v}\| \quad (2.15)$$

$$= -\langle X, \frac{\partial \mathbf{v}}{\partial t} \rangle \quad (2.16)$$

$$= \langle X, -\frac{\partial \mathbf{v}}{\partial t} \rangle \quad (2.17)$$

Identifying  $\left\{ \frac{\partial \mathbf{v}}{\partial u_i} \right\}_{i=1,2}$  as a basis for  $T_u f$ , just as  $\left\{ \frac{\partial f}{\partial u_i} \right\}_{i=1,2}$  is, we can identify a linear transformation  $L : T_u f \rightarrow T_u f$  which converts between bases, i.e.  $L\left(\frac{\partial f}{\partial u_i}\right) = -\frac{\partial \mathbf{v}}{\partial u_i}$ . This allows us to

rewrite the time derivative of the Gauss map as

$$-\frac{d\mathbf{v}}{dt} = \theta'_1(s) \left( -\frac{\partial \mathbf{v}}{\partial u_1} \right) + \theta'_2(s) \left( -\frac{\partial \mathbf{v}}{\partial u_2} \right) \quad (2.18)$$

$$= \theta'_1(s) \left( L \left( -\frac{\partial f}{\partial u_1} \right) \right) + \theta'_2(s) \left( L \left( -\frac{\partial f}{\partial u_2} \right) \right) \quad (2.19)$$

$$= L \left( \theta'_1(s) \left( -\frac{\partial f}{\partial u_1} \right) + \theta'_2(s) \left( -\frac{\partial f}{\partial u_2} \right) \right) \quad (2.20)$$

$$= L \left( \frac{d}{dt} [f(\theta(t))] \right) = L \left( \frac{d}{dt} [c(t)] \right) = L(X) \quad (2.21)$$

With this, we can re-express the curvature of our curve as

$$\|c''\| = \langle X, -\frac{\partial \mathbf{v}}{\partial t} \rangle = \langle X, L(X) \rangle \quad (2.22)$$

which only depends on the point  $u$  and the selected direction  $X$ , not on the particular curve at all! □

In fact, we refer to this quantity as the normal curvature of the surface.

**Definition 2.2.1.** *The normal curvature of a surface at point  $u$  in the direction  $X$  is given by  $\kappa_{\mathbf{v}} := -\langle X, L(X) \rangle$ . In other contexts (not necessary here), this quantity is referred to as the second fundamental form at the point  $u \in U$ ; that is,  $\mathbf{II}(X, X) := -\langle X, L(X) \rangle$ .*

The map  $L$  we used is known as the Weingarten map and is implicitly defined at each  $u \in U$ . We wish to make its existence rigorous as well as find a matrix representation for it, using the standard motivation that  $L(\frac{\partial f}{\partial u_i}) = -\frac{\partial \mathbf{v}}{\partial u_i}$ .

**Definition 2.2.2** (Weingarten map). *The Weingarten map (or shape operator) is the map  $L : T_u f \rightarrow T_u f$  given by  $L = D\mathbf{v} \circ (Df)^{-1}$ .*

That is, we may trace any  $X \in T_u f$  which has been expanded in terms of the basis  $\left\{ \frac{\partial f}{\partial u_1}, \frac{\partial f}{\partial u_2} \right\}$  and expand it along the basis  $\left\{ -\frac{\partial \mathbf{v}}{\partial u_1}, -\frac{\partial \mathbf{v}}{\partial u_2} \right\}$ .

TODO: THIS GOES SOMEWHERE ELSE?? You can simplify by assuming we're dealing with a graph, although it's true in general as long as  $f$  is an immersion. To prove that

$\left\{ \frac{\partial f}{\partial u_1}, \frac{\partial f}{\partial u_2} \right\}$  and  $\left\{ -\frac{\partial v}{\partial u_1}, -\frac{\partial v}{\partial u_2} \right\}$  are each a basis for  $T_u f$ ,

For any immersion,  $\left\{ \frac{\partial f}{\partial u_1}, \frac{\partial f}{\partial u_2} \right\}$  is a linearly independent set. We can directly see that  $f_{u_1}$  and  $f_{u_2}$  are linearly independent in the case of a graph, as  $f_{u_1} = (1, 0, h_{u_2})$  and  $f_{u_2} = (0, 1, h_{u_2})$ , which are clearly linearly independent.

To show that  $\left\{ -\frac{\partial v}{\partial u_1}, -\frac{\partial v}{\partial u_2} \right\}$  is a basis as well, first note that at any particular  $u \in U$ ,  $\langle v, v \rangle = 1 \implies \frac{\partial}{\partial u_i} \langle v, v \rangle = 0$ , and so by chain rule  $2 \langle \frac{\partial v}{\partial u_i}, v \rangle = 0 \implies \frac{\partial v}{\partial u_i} \perp v$ . Since  $v \perp \text{span} \left\{ \frac{\partial f}{\partial u_i} \right\}$  as well (since  $v$  is its outer product), in  $\mathbb{R}^3$ , this implies  $\text{span} \left\{ \frac{\partial v}{\partial u_i} \right\} \parallel \text{span} \left\{ \frac{\partial f}{\partial u_i} \right\}$ .

TODO: why are  $v_{u_i}$  necessarily linearly independent?

TODO: Finish proving soundness of the Weingarten map in the context of a graph

To find a matrix representation for  $L$ , (which we will denote  $\hat{L} \in \mathbb{R}^{2 \times 2}$ ) we simply wish to find a linear transformation such that  $\hat{L} \frac{\partial f}{\partial u_i} \Big|_{T_u f} = - \frac{\partial v}{\partial u_i} \Big|_{T_u f}$  for  $i = 1, 2$

where  $-X|_{T_u f}$  denotes that  $X \in T_u f$  is being represented in a local basis of  $T_u f$ . In matrix form, this translates to

$$\begin{bmatrix} \hat{L} \end{bmatrix} \begin{bmatrix} \uparrow \\ \left[ \frac{\partial f}{\partial u_1} \right]_{T_u f} \\ \downarrow \end{bmatrix} \begin{bmatrix} \uparrow \\ \left[ \frac{\partial f}{\partial u_2} \right]_{T_u f} \\ \downarrow \end{bmatrix} = \begin{bmatrix} \uparrow \\ \hat{L} \left[ \frac{\partial f}{\partial u_1} \right]_{T_u f} \\ \downarrow \end{bmatrix} \begin{bmatrix} \uparrow \\ \hat{L} \left[ \frac{\partial f}{\partial u_2} \right]_{T_u f} \\ \downarrow \end{bmatrix} \quad (2.23)$$

$$= \begin{bmatrix} \uparrow \\ \left[ -\frac{\partial v}{\partial u_1} \right]_{T_u f} \\ \downarrow \end{bmatrix} \begin{bmatrix} \uparrow \\ \left[ -\frac{\partial v}{\partial u_2} \right]_{T_u f} \\ \downarrow \end{bmatrix} \quad (2.24)$$

Now, representing each vector in  $T_u f$  with respect to the basis  $\left\{ \frac{\partial f}{\partial u_i} \right\}$ , we have

$$\implies \begin{bmatrix} \hat{L} \end{bmatrix} \begin{bmatrix} \leftarrow \frac{\partial f}{\partial u_1} \rightarrow \\ \leftarrow \frac{\partial f}{\partial u_2} \rightarrow \end{bmatrix} \begin{bmatrix} \uparrow \\ \frac{\partial f}{\partial u_1} \\ \downarrow \end{bmatrix} \begin{bmatrix} \uparrow \\ \frac{\partial f}{\partial u_2} \\ \downarrow \end{bmatrix} = \begin{bmatrix} \leftarrow \frac{\partial f}{\partial u_1} \rightarrow \\ \leftarrow \frac{\partial f}{\partial u_2} \rightarrow \end{bmatrix} \begin{bmatrix} \uparrow \\ -\frac{\partial v}{\partial u_1} \\ \downarrow \end{bmatrix} \begin{bmatrix} \uparrow \\ -\frac{\partial v}{\partial u_2} \\ \downarrow \end{bmatrix} \quad (2.25)$$

We can simplify this greatly by defining

$$g_{ij} := \left\langle \frac{\partial f}{\partial u_i}, \frac{\partial f}{\partial u_j} \right\rangle \quad \text{and} \quad h_{ij} := \left\langle \frac{\partial f}{\partial u_i}, -\frac{\partial v}{\partial u_j} \right\rangle \quad (2.26)$$

so that

$$\begin{bmatrix} \hat{\mathbf{L}} \end{bmatrix} \begin{bmatrix} g_{11} & g_{12} \\ g_{21} & g_{22} \end{bmatrix} = \begin{bmatrix} h_{11} & h_{12} \\ h_{21} & h_{22} \end{bmatrix} \quad (2.27)$$

Then we rearrange to solve for  $\hat{\mathbf{L}}$  as

$$\hat{\mathbf{L}} = \begin{bmatrix} h_{11} & h_{12} \\ h_{21} & h_{22} \end{bmatrix} \begin{bmatrix} g_{11} & g_{12} \\ g_{21} & g_{22} \end{bmatrix}^{-1} \quad (2.28)$$

Our final goal is to characterize such normal curvatures. Namely, we wish to establish a method of determining in which directions an extremal normal curvature occurs. To do so, we shall consider the relationship between the direction  $X$  and the normal curvature  $\kappa_v$  in that direction at some specified  $u$ .

First, we need the following lemma:

**Lemma 2.2.2.** *If  $A \in R^{n \times n}$  is a symmetric real matrix,  $v \in R^n$  and given the dot product  $\langle \cdot, \cdot \rangle$ , we have  $\nabla_v \langle v, Av \rangle = 2Av$ . In particular, when  $A = I$  the identity matrix, we have  $\nabla_v \langle v, v \rangle = 2v$ .*

*Proof.* The result is uninterestingly obtained by tracking each (the ‘ith’) component of  $\nabla_v \langle v, Av \rangle$ :

$$\left(\nabla_v \langle v, Av \rangle\right)_i = \frac{\partial}{\partial v_i} \left[ \langle v, Av \rangle \right] = \frac{\partial}{\partial v_i} \left[ \sum_{j=1}^n v_j (Av)_j \right] \quad (2.29)$$

$$= \frac{\partial}{\partial v_i} \left[ \sum_{j=1}^n v_j \sum_{k=1}^n a_{jk} v_k \right] \quad (2.30)$$

$$= \frac{\partial}{\partial v_i} \left[ a_{ii} v_i^2 + v_i \sum_{k \neq i} a_{ik} v_k + v_i \sum_{j \neq i} a_{ji} v_j + \sum_{j \neq i} \sum_{k \neq i} v_j a_{jk} v_k \right] \quad (2.31)$$

$$= 2a_{ii} v_i + \sum_{k \neq i} a_{ik} v_k + \sum_{j \neq i} a_{ji} v_j + 0 \quad (2.32)$$

$$= 2a_{ii} v_i + 2 \sum_{k \neq i} a_{ik} v_k = 2 \sum_{k=1}^n a_{ik} v_k = 2(Av)_i \quad (2.33)$$

$$\implies \nabla_v \langle v, Av \rangle = 2Av. \quad (2.34)$$

□

We are now ready for the major result of this section.

**Theorem 2.2.3** (Theorem of Olinde Rodrigues). *Fixing a point  $u \in U$ , a direction  $X \in T_u f$  minimizes the normal curvature  $\kappa_v = \langle LX, X \rangle$  subject to  $\langle X, X \rangle = 1$  iff  $X$  is a (normalized) eigenvector of the Weingarten map  $L$ .*

*Proof.* In the following, we will assume that  $X \in T_u f$  is expanded, in local coordinates, i.e. along a two dimensional basis (such as  $\left\{ \frac{\partial f}{\partial u_i} \right\}_{i=1,2}$ ) and thus can refer to  $L$  freely as the  $2 \times 2$  matrix  $\widehat{L}$ . Using the method of Lagrange multipliers, we define the Lagrangian:

$$\mathcal{L}(X; \lambda) = \langle \widehat{L}X, X \rangle - \lambda (\langle X, X \rangle - 1) \quad (2.35)$$

Extremal values occur when  $\nabla_{X, \lambda} \mathcal{L}(X; \lambda) = 0$ , which becomes the two equations

$$\begin{cases} \nabla_X \langle \widehat{L}X, X \rangle - \lambda \nabla_X (\langle X, X \rangle - 1) = 0 \\ \langle X, X \rangle - 1 = 0 \end{cases} \quad (2.36)$$

The second requirement is simply the constraint that  $X$  is normalized. Using the previous lemma, we can simplify the first result as follows:

$$\nabla_X \langle \hat{L}X, X \rangle - \lambda \nabla_X (\langle X, X \rangle - 1) = 0 \quad (2.37)$$

$$2\hat{L}X - \lambda(2X) = 0 \quad (2.38)$$

$$\implies \hat{L}X - \lambda X = 0 \implies \hat{L}X = \lambda X \quad (2.39)$$

which implies that  $X$  is an eigenvector of *weinmat* with corresponding eigenvalue  $\lambda$ . Thus the two hypotheses are exactly equivalent when  $X$  is normalized. It is also worth remarking that the corresponding eigenvalue  $\lambda$  is the Lagrangian multiplier itself.  $\square$

Thus, to find the directions of greatest and least curvature of a surface at a point  $u \in U$ , we simply must calculate the Weingarten map and its eigenvectors. We refer to these directions as follows.

**Definition 2.2.3** (Principal Curvatures and Principal Directions). *The extremal values of normal curvature of a surface at a point  $u \in U$  are referred to as **principal curvatures**. The corresponding directions at which normal curvature attains an extremal value are referred to as **principal directions**.*

Our final goal is to explicitly determine a (hopefully simplified) version of the Weingarten map in the case of a graph  $f(u_1, u_2) = (u_1, u_2, h(u_1, u_2))$  and calculate the principal directions and curvatures in a simple example.

**Theorem 2.2.4.** *When  $f : U \rightarrow \mathbb{R}^3$  is given by  $(u_1, u_2) \mapsto (u_1, u_2, h(u_1, u_2))$ , the matrix representation of the Weingarten map is exactly the Hessian matrix given in (2.1) has the same principal directions as the eigenvectors of  $\text{Hess}(h)$ , and the principal directions of  $f$  are proportional to the eigenvalues of  $\text{Hess}(h)$ .*

*Proof.* First, we can (using chain rule) rewrite each component as

$$\left\langle \frac{\partial f}{\partial u_i}, -\frac{\partial \mathbf{v}}{\partial u_j} \right\rangle = \left\langle \frac{\partial^2 f}{\partial u_i \partial u_j}, \mathbf{v} \right\rangle$$

Now, given our particular surface  $f$ , we can calculate each of these components directly.

We have:

$$f_u = (1, 0, L_u), \quad f_v = (0, 1, L_v) \quad (2.40)$$

$$f_{uu} = (0, 0, L_{uu}), \quad f_{uv} = (0, 0, L_{uv}) = f_{vu}, \quad f_{vv} = (0, 0, L_{vv})$$

and we have the unit normal vector (Gauss map)

$$\mathbf{v}(u_1, u_2) = \frac{\frac{\partial f}{\partial u_1} \times \frac{\partial f}{\partial u_2}}{\left\| \frac{\partial f}{\partial u_1} \times \frac{\partial f}{\partial u_2} \right\|} \quad (2.41)$$

$$= \frac{(1, 0, L_u) \times (0, 1, L_v)}{\|\cdots\|} \quad (2.42)$$

□

## Calculating Derivatives of Discrete Images

Discrete derivatives. **✂TODO:** Develop the following:

- Take derivative with gradient / divided difference.
- Derivatives should be taken on Gaussian blur (equivalent to scale space development) [Lindeberg]. That is, you can take the derivative of either the convolved image, or you can take derivatives of the Gaussian itself, *then* convolve.
- Pseudocode for `np.gradient` which is used in calculating Hessian (code below)

```
gaussian_filtered = fftgauss(image, sigma=sigma)
Lx, Ly = np.gradient(gaussian_filtered)
Lxx, Lxy = np.gradient(Lx)
Lxy, Lyy = np.gradient(Ly)
```

## The Frangi Filter

### Intro to Hessian-based filters

Hessian-based filters are a family of curvilinear filters that employ the Hessian and its eigenspaces to determine regions of significant curvature within an image. Several such filters exist –see Sato [13] and Lorenz[10]. These filters use information about the principal curvatures (eigenvalues of the Hessian) at each point to

### Overview of Frangi vesselness measure

The Frangi filter is a widely used [citation needed] Hessian-based filter that relies on the principal curvatures—that is, the eigenvalues of  $\mathcal{H}_\sigma(x,y)$  at some particular scale  $\sigma$  at each point  $(x,y)$  in the image.

### Implementation Details: Convolution Speedup via FFT

As described above, the actual computation of derivatives is achieved via convolution with a gaussian. In practice, this is very slow for large scales. In **TODO**.

- find image processing papers that find hessian from FFT / who uses this?
- with above: downsides?
- SIDE BY SIDE comparison?

### 2D Discrete Fourier Transform Convolution Theorem . <sup>2</sup>

**Theorem 2.4.1** (2D DFT Convolution Theorem). *Given two discrete functions are sequences with the same length<sup>3</sup>, that is:  $f(x,y)$  and  $h(x,y)$  for integers  $0 < x < M$  and  $0 < y < N$ , we can*

---

<sup>2</sup>the following was adapted in a large part from DFT: an owner's manual. cite?

<sup>3</sup>If they're not actually the same length, DIP-GW suggests to make the final length at least  $P = A + C - 1$  and  $Q = B + D - 1$  in the case that the sizes are  $A \times B$  and  $C \times D$  for  $f(x,y)$  and  $h(x,y)$  respectively. Not sure if that matters.



take the discrete fourier transform (DFT) of each:

$$F(u, v) := \mathcal{D}\{f(x, y)\} = \sum_{x=0}^{M-1} \sum_{y=0}^{N-1} f(x, y) e^{-2\pi i \left( \frac{ux}{M} + \frac{vy}{N} \right)} \quad (2.43)$$

$$H(u, v) := \mathcal{D}\{h(x, y)\} = \sum_{x=0}^{M-1} \sum_{y=0}^{N-1} h(x, y) e^{-2\pi i \left( \frac{ux}{M} + \frac{vy}{N} \right)} \quad (2.44)$$

and given the convolution of the two functions

$$(f \star h)(x, y) = \sum_{m=0}^{M-1} \sum_{n=0}^{N-1} f(m, n) h(x-m, y-n) \quad (2.45)$$

then  $(f \star h)(x, y)$  and  $MN \cdot F(u, v)H(u, v)$  are transform pairs, i.e.

$$(f \star h)(x, y) = \mathcal{D}^{-1} \{MN \cdot F(u, v)H(u, v)\} \quad (2.46)$$

The proof follows from the definition of convolution, substituting in the inverse-DFT of  $f$  and  $h$ , and then rearrangement of finite sums.

*Proof.*

$$(f \star h)(x, y) = \sum_{m=0}^{M-1} \sum_{n=0}^{N-1} f(m, n) h(x-m, y-n) \quad (2.47)$$

$$= \sum_{m=0}^{M-1} \sum_{n=0}^{N-1} \left( \sum_{p=0}^{M-1} \sum_{q=0}^{N-1} F(p, q) e^{2\pi i \left( \frac{mp}{M} + \frac{nq}{N} \right)} \right) \left( \sum_{u=0}^{M-1} \sum_{v=0}^{N-1} H(u, v) e^{2\pi i \left( \frac{u(x-m)}{M} + \frac{v(y-n)}{N} \right)} \right) \quad (2.48)$$

$$= \left( \sum_{u=0}^{M-1} \sum_{v=0}^{N-1} H(u, v) e^{2\pi i \left( \frac{ux}{M} + \frac{vy}{N} \right)} \right) \left( \sum_{p=0}^{M-1} \sum_{q=0}^{N-1} F(p, q) \left( \sum_{m=0}^{M-1} e^{2\pi i \left( \frac{m(p-u)}{M} \right)} \right) \left( \sum_{n=0}^{N-1} e^{2\pi i \left( \frac{n(q-v)}{N} \right)} \right) \right) \quad (2.49)$$

$$= \left( \sum_{u=0}^{M-1} \sum_{v=0}^{N-1} H(u, v) e^{2\pi i \left( \frac{ux}{M} + \frac{vy}{N} \right)} \right) \left( \sum_{p=0}^{M-1} \sum_{q=0}^{N-1} F(p, q) \left( M \cdot \hat{\delta}_M(p-u) \right) \left( N \cdot \hat{\delta}_N(q-v) \right) \right) \quad (2.50)$$

$$= \left( \sum_{u=0}^{M-1} \sum_{v=0}^{N-1} H(u, v) e^{2\pi i \left( \frac{ux}{M} + \frac{vy}{N} \right)} \right) \cdot MN F(u, v) \quad (2.51)$$

$$= MN \cdot \sum_{u=0}^{M-1} \sum_{v=0}^{N-1} F(u, v) H(u, v) e^{2\pi i \left( \frac{ux}{M} + \frac{vy}{N} \right)} \quad (2.52)$$

$$= MN \cdot \mathcal{D}^{-1} \{FH\} \quad (2.53)$$

where

$$\hat{\delta}_N(k) = \begin{cases} 1 & \text{when } k \equiv 0 \pmod{N} \\ 0 & \text{else} \end{cases} \quad (2.54)$$

□

Above, we make use of the following lemma:

**Lemma 2.4.2.** *Let  $j$  and  $k$  be integers and let  $N$  be a positive integer. Then*

$$\sum_{n=0}^{N-1} e^{2\pi i \left( \frac{n(j-k)}{N} \right)} = N \cdot \hat{\delta}_N(j-k) \quad (2.55)$$

*Proof.* For any particular  $n \in 0..N-1$ , consider the complex number  $e^{2\pi i n(j-k)/N}$ . Note first, that this is an  $N$ -th root of unity, since

$$\left( e^{2\pi i n(j-k)/N} \right)^N = e^{2\pi i n(j-k)} = (e^{2\pi i})^{n(j-k)} = 1^{n(j-k)} = 1$$

Thus, we understand that the complex number  $e^{2\pi i n(j-k)/N}$  is a root of  $z^N - 1 = 0$ , which we rewrite as

$$z^N - 1 = (z-1)(z^{N-1} + \cdots + z + 1) = (z-1) \sum_{n=0}^{N-1} z^n.$$

We consider two cases: in the case that  $j-k$  is a multiple of  $N$ , we of course have  $e^{2\pi i n(j-k)/N} = 1$  for any  $n$ , and thus

$$\sum_{n=0}^{N-1} e^{2\pi i \left( \frac{n(j-k)}{N} \right)} = \sum_{n=0}^{N-1} (1) = N$$

.

In the case that  $j-k$  is *not* a multiple of  $N$ , then clearly  $\left( e^{2\pi i n(j-k)/N} \right) - 1 \neq 0$ , and thus it must be that

$$\left( e^{2\pi i n(j-k)/N} \right)^N - 1 = 0 \implies \sum_{n=0}^{N-1} \left( e^{2\pi i n(j-k)/N} \right)^n = 0$$

Combining these two cases gives the result of the lemma. □

## FFT .

As noted, the above result applies to the Discrete Fourier Transform. As noted, we actually achieve a convolution speedup using a Fast Fourier Transform (FFT) instead.

- Basic theory.
- Show speedup and equivalency.

## Odds & Ends of Fourier Analysis .

- Sampling theory?
- Wraparound error?
- Any other kinks introduced in going from continuous to discrete.

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## Linear Scale Space Theory

Koenderink showed/asserted that "any image can be embedded in a one-parameter family of derived images (with resolution as the parameter) in essentially only one unique way" given a few of the so-called *scale space axioms*. They showed in particular that any such family must satisfy the heat equation

$$\Delta K(x, y, \sigma) = K_{\sigma}(x, y, \sigma) \text{ for } \sigma \geq 0 \text{ such that } K(x, y, 0) = u_0(x, y). \quad (2.56)$$

where  $K : \mathbb{R}^3 \rightarrow \mathbb{R}$  and  $u_0 : \mathbb{R}^2 \rightarrow \mathbb{R}$  : is the original image (viewed as a continuous surface) and  $\sigma$  is a resolution parameter. Much work blah blah blah has been done to formalize this approach.

## Significance of the convolution operation

This section shows that if one constructs the family using an operation and a source image, the necessary operation is necessarily equivalent to convolution. I am guessing at this, but I think the axiom that causes this is wanting no space in the image to be preferred.

## Uniqueness of the Gaussian Kernel

This is the result of most of these axioms.

### $G_\sigma \star u_0$ solves the heat equation

given  $u_0$  as a continuous image (unscaled), we construct PDE with this as a boundary condition.

$$u : \mathbb{R}^2 \supset \Omega \rightarrow \mathbb{R} \text{ with } u(\mathbf{x}, t) : \begin{cases} \frac{\partial u}{\partial t}(\mathbf{x}, t) = \Delta u(\mathbf{x}, t) & , t \geq 0 \\ u(\mathbf{x}, 0) = u_0(\mathbf{x}) \end{cases} \quad (2.57)$$

We show that

$$u(\mathbf{x}, t) = \left( G_{\sqrt{2t}} \star u_0 \right) (\mathbf{x}) \quad (2.58)$$

solves (the above tagged equation), where

$$G_\sigma := \frac{1}{2\pi\sigma^2} e^{(-|\mathbf{x}|^2/(2\sigma^2))}$$

First, we need a quick lemma regarding differentiation a continuous convolution.

**Lemma 2.5.1.** *Derivative of a convolution is the way that it is (obviously rewrite this).*

*Proof.* For a single variable,

$$\frac{\partial}{\partial \alpha} [f(\alpha) \star g(\alpha)] = \frac{\partial}{\partial \alpha} \left[ \int f(t) g(\alpha - t) dt \right] \quad (2.59)$$

$$= \int f(t) \frac{\partial}{\partial \alpha} [g(\alpha - t)] dt \quad (2.60)$$

$$= \int f(t) \left( \frac{\partial g}{\partial \alpha} \right) g(\alpha - t) dt \quad (2.61)$$

$$= f(\alpha) \star g'(\alpha) \quad (2.62)$$

By symmetry of convolution we can also conclude

$$\frac{\partial}{\partial \alpha} [f(\alpha) \star g(\alpha)] = f'(\alpha) \star g(\alpha)$$

If  $f$  and  $g$  are twice differentiable, we can compound this result to show a similar statement holds for second derivatives, and then, given the additivity of convolution, we may conclude

$$\Delta(f \star g) = \Delta(f) \star g = f \star \Delta(g) \quad (2.63)$$

□

**Theorem 2.5.2.**  $u(\mathbf{x}, t) = \left( G_{\sqrt{2t}} \star u_0 \right)(\mathbf{x})$  solves the heat equation.

*Proof.* We focus on the particular kernel

$$G_{\sqrt{2t}} = \frac{1}{4\pi t} e^{(-|\mathbf{x}|^2/(4t))}$$

Then

$$\frac{\partial u}{\partial t}(\mathbf{x}, t) = \frac{\partial}{\partial t} \left( G_{\sqrt{2t}}(\mathbf{x}, t) \star u_0(\mathbf{x}) \right) \quad (2.64)$$

$$= \frac{\partial}{\partial t} \left( G_{\sqrt{2t}}(\mathbf{x}, t) \right) \star u_0(\mathbf{x}) \quad (2.65)$$

$$= \frac{\partial}{\partial t} \left( \frac{1}{4\pi t} e^{(-|\mathbf{x}|^2/(4t))} \right) \star u_0(\mathbf{x}) \quad (2.66)$$

$$= \left[ -\frac{1}{4\pi t^2} e^{(-|\mathbf{x}|^2/(4t))} + \frac{1}{4\pi t} \left( \frac{-|\mathbf{x}|^2}{4t^2} \right) e^{(-|\mathbf{x}|^2/(4t))} \right] \star u_0(\mathbf{x}) \quad (2.67)$$

$$= -\frac{1}{4t^2} \left( e^{(-|\mathbf{x}|^2/(4t))} + |\mathbf{x}|^2 G_{\sqrt{2t}}(\mathbf{x}, t) \right) \star u_0(\mathbf{x}) \quad (2.68)$$

and from the previous lemma,

$$\Delta u(\mathbf{x}, t) = \Delta \left( G_{\sqrt{2t}} \star u_0(\mathbf{x}) \right) = \Delta \left( G_{\sqrt{2t}} \right) \star u_0(\mathbf{x})$$

We explicitly calculate the Laplacian of  $G_{\sigma}(x, y) = A \exp(-\frac{x^2+y^2}{2\sigma^2})$  as follows:

$$\begin{aligned}
\frac{\partial}{\partial x} G_{\sigma}(x, y) &= A \left( \frac{-2x}{2\sigma^2} \right) \exp \left( -\frac{x^2 + y^2}{2\sigma^2} \right) \\
\Rightarrow \frac{\partial^2}{\partial^2 x} G_{\sigma}(x, y) &= A \cdot \frac{\partial}{\partial x} \left[ -\frac{x}{\sigma^2} \exp \left( -\frac{x^2 + y^2}{2\sigma^2} \right) \right] \\
&= A \left[ -\frac{1}{\sigma^2} \exp \left( -\frac{x^2 + y^2}{2\sigma^2} \right) + \frac{x}{\sigma^2} \cdot \frac{2x}{2\sigma^2} \exp \left( -\frac{x^2 + y^2}{2\sigma^2} \right) \right] \\
&= A \exp \left( -\frac{x^2 + y^2}{2\sigma^2} \right) \left[ -\frac{1}{\sigma^2} + \frac{x^2}{\sigma^4} \right] \\
&= \frac{1}{\sigma^2} G_{\sigma}(x, y) \left[ \frac{x^2}{\sigma^2} - 1 \right]
\end{aligned}$$

By symmetry of argument we also may conclude

$$\frac{\partial^2}{\partial y^2} G_{\sigma}(x, y) = \frac{1}{\sigma^2} G_{\sigma}(x, y) \left[ \frac{y^2}{\sigma^2} - 1 \right]$$

and so

$$\Delta G_{\sigma}(x, y) = \frac{\partial^2}{\partial x^2} (G_{\sigma}) + \frac{\partial^2}{\partial y^2} (G_{\sigma}) = \frac{1}{\sigma^2} G_{\sigma}(x, y) \left[ \frac{x^2 + y^2}{\sigma^2} - 2 \right] \quad (2.69)$$

Then, given lemma 2.5.1, we conclude

$$\Delta [G_{\sigma}(x, y) \star u_0(x, y)] = \left( \frac{1}{\sigma^2} G_{\sigma}(x, y) \left[ \frac{x^2 + y^2}{\sigma^2} - 2 \right] \right) \star u_0(x, y) \quad (2.70)$$

For particular choices of  $\sigma(t) = \sqrt{2t}$  and  $A = \frac{1}{4\pi t}$ , we see

$$\Delta \left[ G_{\sqrt{2t}}(x, y) \star u_0(x, y) \right] = \left( \frac{1}{2t} G_{\sqrt{2t}}(x, y) \left[ \frac{x^2 + y^2}{2t} - 2 \right] \right) \star u_0(x, y) \quad (2.71)$$

$$= \left( G_{\sqrt{2t}}(x, y) \left[ \frac{x^2 + y^2}{4t^2} - \frac{1}{t} \right] \right) \star u_0(x, y) \quad (2.72)$$

We then calculate the time derivative, using our particular choice of  $\sigma(t) = \sqrt{2t}$  and  $A = \frac{1}{4\pi t}$  as:

$$\frac{\partial}{\partial t} [G_{\sigma(t)}(x, y) \star u_0(x, y)] = \frac{\partial}{\partial t} [G_{\sigma(t)}(x, y)] \star u_0(x, y) \quad (2.73)$$

$$= \frac{\partial}{\partial t} [G_{\sqrt{2t}}(x, y)] \star u_0(x, y) \quad (2.74)$$

$$= \frac{\partial}{\partial t} \left[ \frac{1}{4\pi t} \exp\left(-\frac{x^2 + y^2}{4t}\right) \right] \star u_0(x, y) \quad (2.75)$$

$$= \left[ -\frac{1}{4\pi t^2} \exp\left(-\frac{x^2 + y^2}{4t}\right) + \frac{1}{4\pi t} \left( \frac{x^2 + y^2}{4t^2} \exp\left(-\frac{x^2 + y^2}{4t}\right) \right) \right] \star u_0(x, y) \quad (2.76)$$

$$= \left( G_{\sqrt{2t}}(x, y) \left[ \frac{x^2 + y^2}{4t^2} - \frac{1}{t} \right] \right) \star u_0(x, y) \quad (2.77)$$

Combining these results, we find that

$$\frac{\partial}{\partial t} [G_{\sqrt{2t}} \star u_0] = \Delta [G_{\sqrt{2t}} \star u_0] \quad (2.78)$$

as desired. □

---

## Morphology

Methods of merging multiscale methods.

---

## Other Odds and Ends

Finding the placental plate. Preprocessing. Could go in next section as well.

## **CHAPTER 3**

### **RESEARCH PROTOCOL**

List. All. Decisions. You Make. Be very explicit.

Pseudocode?



## **CHAPTER 4**

### **RESULTS AND ANALYSIS**

#### **Data Set**

Specifics of your data set. Barium placentas, other datasets.

NOTE: FIND YOUR TRACING PROTOCOL.

NOTE: Be specific about each so it's easy to gauge for others whether or not these methods would apply to their own research

Preprocessing

#### **Results**

Show stuff who the fuck knows

#### **Answer Research Questions**

## **CHAPTER 5**

### **CONCLUSION**

What it did well. What it didn't. People who want to expand—where should they start?

## APPENDICES

**APPENDIX A**  
**APPENDIX TITLE**

Put code here (and on github)

## BIBLIOGRAPHY

## BIBLIOGRAPHY

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