

Edge Detection from Fourier Phase Data

Alexander Reynolds
Advisor Dr. Anne Gelb

Arizona State University
School of Mathematical and Statistical Sciences

2016 Southwestern Undergraduate Mathematics Research Conference



Overview

1 Introduction

- Edge Detection
- Fourier Analysis Background
- Concentration Factor Method

2 Recent Results

3 Current Work

- Fourier Phase Data
- Analysis
- Computational Examples

4 Future Work

5 Acknowledgements



What is Edge Detection?

Example: Edge Detection on an Image



Applications of Edge Detection

Primary applications:

- Magnetic Resonance Imaging (MRI)



Applications of Edge Detection

Primary applications:

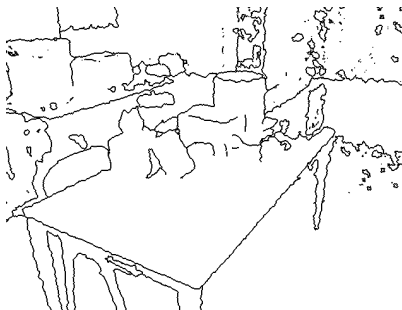
- Magnetic Resonance Imaging (MRI)
- Synthetic Aperture Radar (SAR)



Applications of Edge Detection

Primary applications:

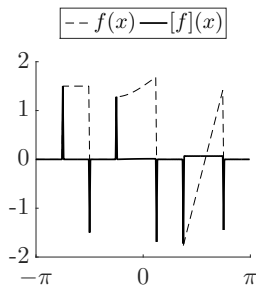
- Magnetic Resonance Imaging (MRI)
- Synthetic Aperture Radar (SAR)
- Computer/Machine Vision (e.g. Kinect)



Applications of Edge Detection

Primary applications:

- Magnetic Resonance Imaging (MRI)
- Synthetic Aperture Radar (SAR)
- Computer/Machine Vision (e.g. Kinect)
- 1-D Case: Discontinuities of a Function



Fourier Analysis and Synthesis

A Fourier series is a harmonic expansion of a periodic function

Fourier Series (Synthesis)

$$f(x) = \sum_{k=-\infty}^{\infty} \hat{f}_k e^{ikx}$$

$$S_N f(x) = \sum_{k=-N}^N \hat{f}_k e^{ikx}$$

Fourier Analysis and Synthesis

A Fourier series is a harmonic expansion of a periodic function

Fourier Series (Synthesis)

$$f(x) = \sum_{k=-\infty}^{\infty} \hat{f}_k e^{ikx} \qquad S_N f(x) = \sum_{k=-N}^N \hat{f}_k e^{ikx}$$

where the **Fourier coefficients** \hat{f}_k are given by the Fourier transform of f .

Fourier Transform (Analysis)

$$\hat{f}_k = \frac{1}{2\pi} \int_{-\pi}^{\pi} f(x) e^{-ikx} dx$$

Convolution

We can also express $S_N f(x)$ via convolution

Convolution with the Dirichlet Kernel

$$(f * D_N)(x) = \frac{1}{2\pi} \int_{-\pi}^{\pi} f(y) D_N(x - y) dy = S_N f(x)$$

where D_N is the N -th Dirichlet Kernel, given by

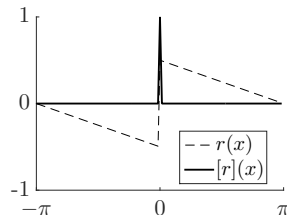
Dirichlet Kernel

$$D_N(x) = \sum_{k=-N}^N e^{ikx}$$

Concentration Edge Detection Method

Define the **jump function** of f , $[f](x)$, as the difference between the right and left hand limits of the function f at every point x ; viz.,

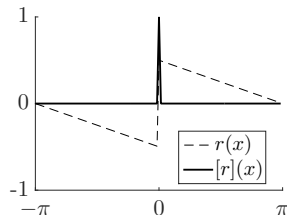
$$[f](x) = f(x^+) - f(x^-).$$



Concentration Edge Detection Method

Define the **jump function** of f , $[f](x)$, as the difference between the right and left hand limits of the function f at every point x ; viz.,

$$[f](x) = f(x^+) - f(x^-).$$



There exists a relationship between these limits and the Fourier partial sum approximation $S_N f(x)$

Dirichlet's Theorem (1824)

$$(f * D_N)(x) = S_N f(x) = \sum_{k=-N}^N \hat{f}_k e^{ikx} \longrightarrow \frac{1}{2} (f(x^+) + f(x^-))$$

Concentration Edge Detection Method (cont.)

The edge detection method developed by Gelb and Tadmor (1999) introduces a function $\sigma(k)$, called a **concentration factor**, which modifies the Dirichlet kernel to *concentrate* the partial sum along the singular support of the underlying function.



Concentration Edge Detection Method (cont.)

The edge detection method developed by Gelb and Tadmor (1999) introduces a function $\sigma(k)$, called a **concentration factor**, which modifies the Dirichlet kernel to *concentrate* the partial sum along the singular support of the underlying function.

Concentration Factor Jump Detector

$$(f * K_N)(x) = S_N^\sigma[f](x) = \sum_{k=-N}^N \sigma(k) \hat{f}_k e^{ikx} \longrightarrow [f](x)$$

Analytical Concentration Factors

Examples of some analytical concentration factors:

Factor	Expression	Remarks
Trigonometric	$\sigma(\eta) = \frac{\pi \sin(\pi\eta)}{\text{Si}(\pi)}$	$\text{Si}(\pi) = \int_0^\pi \frac{\sin(x)}{x} dx$
Polynomial	$\sigma(\eta) = p\pi\eta^p$	p is the order of the factor
Exponential	$\sigma(\eta) = C\eta e^{\frac{1}{\alpha\eta(\eta-1)}}$	α is the order C is a normalizing constant $\frac{\pi}{C} = \int_{\frac{1}{N}}^{1-\frac{1}{N}} \exp\left(\frac{1}{\alpha\tau(\tau-1)}\right) d\tau$

Jump Reconstruction from Fourier Data

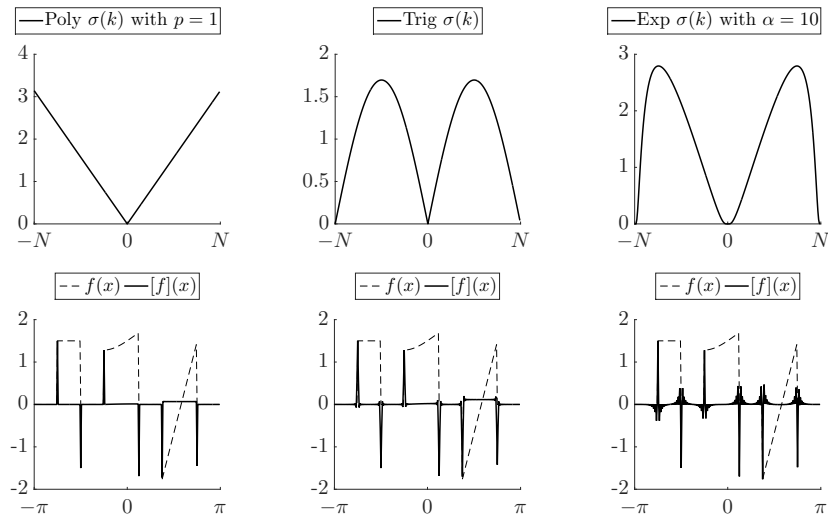


Figure: $S_N[f](x)$ with various concentration factors σ .

Designed Concentration Factors

How can we design *other* concentration factors?



Designed Concentration Factors

How can we design *other* concentration factors? We want

Partial Sum Approximation of $[f](x)$

$$S_N^\sigma[f](x) = \sum_{k=-N}^N \sigma(k) \hat{f}_k e^{ikx} \longrightarrow [f](x).$$

Designed Concentration Factors

How can we design *other* concentration factors? We want

Partial Sum Approximation of $[f](x)$

$$S_N^\sigma[f](x) = \sum_{k=-N}^N \sigma(k) \hat{f}_k e^{ikx} \longrightarrow [f](x).$$

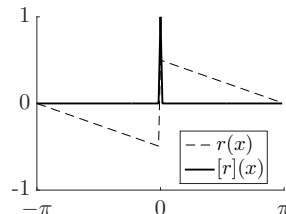
We can engineer σ for a function $g(x)$ where we know what $[g](x)$ is.

Designed Concentration Factors (cont.)

Consider the ramp function $r(x)$ with the associated jump function $[r](x)$ on the interval $[-\pi, \pi)$:

$$r(x) = \begin{cases} \frac{1}{2\pi}(-x - \pi) & \text{if } x < 0, \\ \frac{1}{2\pi}(-x + \pi) & \text{if } x \geq 0. \end{cases}$$

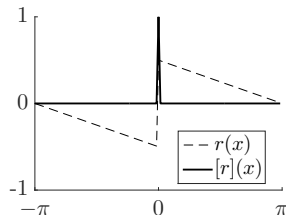
$$[r](x) = \begin{cases} 1 & \text{if } x = 0, \\ 0 & \text{otherwise.} \end{cases}$$



Designed Concentration Factors (cont.)

Consider the ramp function $r(x)$ with the associated jump function $[r](x)$ on the interval $[-\pi, \pi)$:

$$r(x) = \begin{cases} \frac{1}{2\pi}(-x - \pi) & \text{if } x < 0, \\ \frac{1}{2\pi}(-x + \pi) & \text{if } x \geq 0. \end{cases}$$
$$[r](x) = \begin{cases} 1 & \text{if } x = 0, \\ 0 & \text{otherwise.} \end{cases}$$



Partial Sum Approximation of $[r](x)$

$$S_N^\sigma[r](x) = \sum_{k=-N}^N \sigma(k) \hat{r}_k e^{ikx} \longrightarrow [r](x)$$

Designed Concentration Factors (cont.)

We can solve the system $S\sigma = [r](x)$ for a solution $\sigma(k)$ to the equation

$$S_N^\sigma[f](x) = \sum_{k=-N}^N \sigma(k) \hat{f}_k e^{ikx} \longrightarrow [f](x)$$

Designed Concentration Factors (cont.)

We can solve the system $S\sigma = [r](x)$ for a solution $\sigma(k)$ to the equation

$$S_N^\sigma[f](x) = \sum_{k=-N}^N \sigma(k) \hat{f}_k e^{ikx} \longrightarrow [f](x)$$

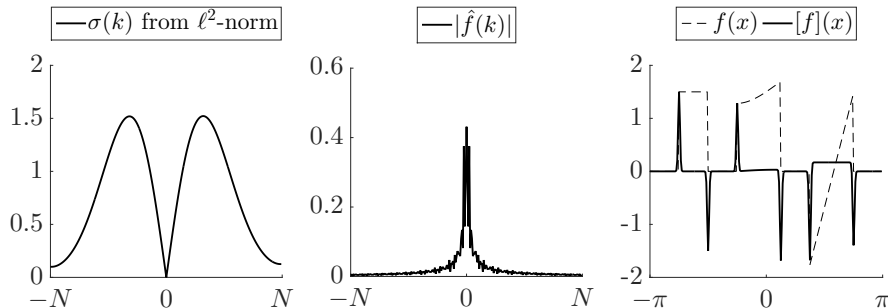


Figure: $S_N[f](x)$ from σ and \hat{f}

Fourier Phase Data

What is Fourier Phase Data?



Fourier Phase Data

What is Fourier Phase Data? Recall

Fourier Series

$$f(x) = \sum_{k=-\infty}^{\infty} \hat{f}_k e^{ikx}, \text{ where } \hat{f}_k = \frac{1}{2\pi} \int_{-\pi}^{\pi} f(x) e^{-ikx} dx.$$

The Fourier coefficients \hat{f}_k are complex numbers, i.e., $\hat{f}_k = \alpha_k e^{i\theta_k}$, where α_k is the **amplitude** and $e^{i\theta_k}$ is the **phase**.

Fourier Phase Data

What is Fourier Phase Data? Recall

Fourier Series

$$f(x) = \sum_{k=-\infty}^{\infty} \hat{f}_k e^{ikx}, \text{ where } \hat{f}_k = \frac{1}{2\pi} \int_{-\pi}^{\pi} f(x) e^{-ikx} dx.$$

The Fourier coefficients \hat{f}_k are complex numbers, i.e., $\hat{f}_k = \alpha_k e^{i\theta_k}$, where α_k is the **amplitude** and $e^{i\theta_k}$ is the **phase**.

Let \tilde{f}_k be the Fourier phase data, i.e., $\tilde{f}_k = \frac{\hat{f}_k}{\|\hat{f}_k\|} = e^{i\theta_k}$.

Fourier Phase Data

What is Fourier Phase Data? Recall

Fourier Series

$$f(x) = \sum_{k=-\infty}^{\infty} \hat{f}_k e^{ikx}, \text{ where } \hat{f}_k = \frac{1}{2\pi} \int_{-\pi}^{\pi} f(x) e^{-ikx} dx.$$

The Fourier coefficients \hat{f}_k are complex numbers, i.e., $\hat{f}_k = \alpha_k e^{i\theta_k}$, where α_k is the **amplitude** and $e^{i\theta_k}$ is the **phase**.

Let \tilde{f}_k be the Fourier phase data, i.e., $\tilde{f}_k = \frac{\hat{f}_k}{\|\hat{f}_k\|} = e^{i\theta_k}$.

Is it still possible to reconstruct the jumps from \tilde{f}_k ?



Jump Location from Fourier Phase

Suppose f is a 2π -periodic function on $[-\pi, \pi)$ with a single jump discontinuity at $x = \xi$. Integration by parts reveals a relationship Fourier coefficients of f and the jump function $[f]$.

Fourier Coefficients

$$\begin{aligned}\hat{f}_k &= \frac{1}{2\pi} \int_{-\pi}^{\pi} f(x) e^{-ikx} dx \\ &\approx \frac{[f](\xi) e^{-ik\xi}}{2\pi i k} + \mathcal{O}\left(\frac{1}{k^2}\right) \\ &\approx \frac{[f](\xi)}{2\pi k} e^{-i(k\xi + \pi/2)}\end{aligned}$$

Jump Reconstruction from Fourier Phase Data

We can again solve the system $S\tilde{\sigma} = [r](x)$ for a solution $\tilde{\sigma}$ to

$$S_N^{\tilde{\sigma}}[f](x) = \sum_{k=-N}^N \tilde{\sigma}(k) \tilde{f}_k e^{ikx} \longrightarrow [f](x)$$

Jump Reconstruction from Fourier Phase Data

We can again solve the system $S\tilde{\sigma} = [r](x)$ for a solution $\tilde{\sigma}$ to

$$S_N^{\tilde{\sigma}}[f](x) = \sum_{k=-N}^N \tilde{\sigma}(k) \tilde{f}_k e^{ikx} \longrightarrow [f](x)$$

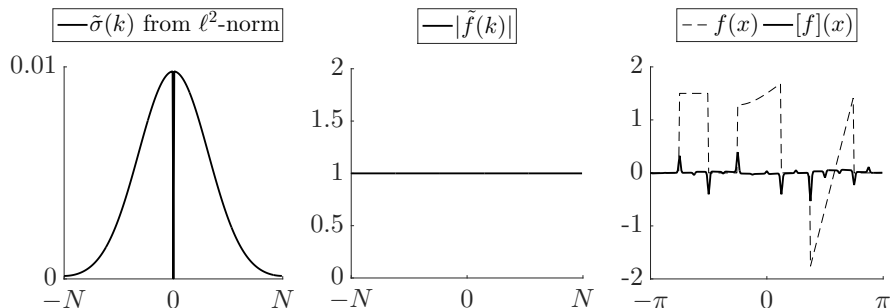


Figure: Reconstruction of $[f](x)$ from $\tilde{\sigma}$ and \tilde{f}

Jump Reconstruction from Fourier Phase Data

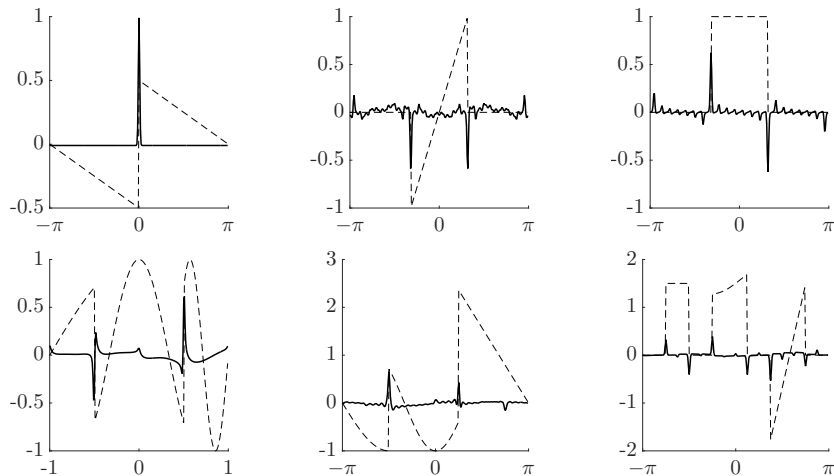


Figure: Reconstructions of multiple functions from $\tilde{\sigma}$ and \tilde{f} .

Noisy Data

We used the MATLAB command `awgn(data,SNR)` to generate additive white Gaussian (complex) noise onto the Fourier data.



Noisy Data

We used the MATLAB command `awgn(data,SNR)` to generate additive white Gaussian (complex) noise onto the Fourier data.

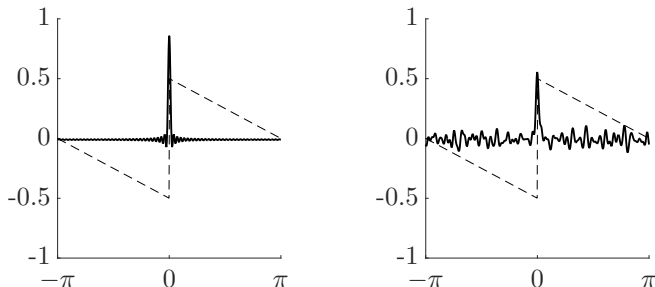


Figure: Ramp jump approximation with and without noise

Noisy Data

We used the MATLAB command `awgn(data,SNR)` to generate additive white Gaussian (complex) noise onto the Fourier data.

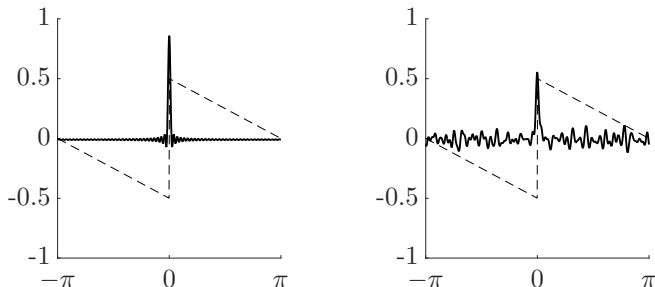


Figure: Ramp jump approximation with and without noise

We can compare how different concentration factors hold up in different levels of noise.

Noisy Phase Data Jump Approximations

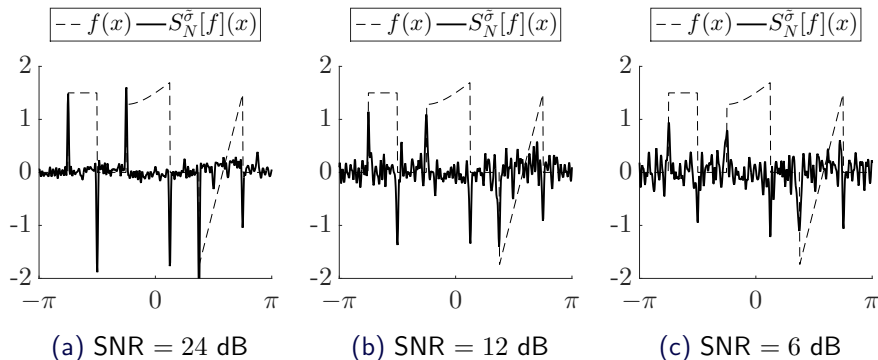


Figure: Jump approximations given noisy Fourier phase data using analytical trigonometric $\tilde{\sigma}$.

Noisy, Banded Phase Data Jump Approximations

Finally, we can consider noisy, banded Fourier phase data

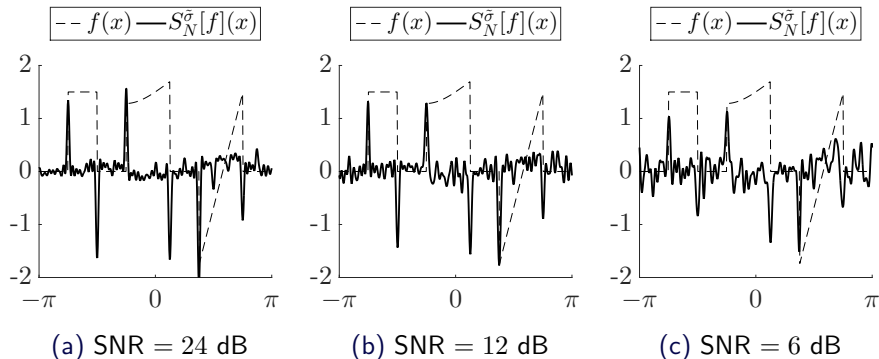


Figure: Jump approximations given noisy, low-frequency banded Fourier phase data using the designed $\tilde{\sigma}$ from ℓ_2 -norm.

Future Work

Computational possibilities:

- Combining multiple (orthogonal) concentration factors
- Generalizations to two dimensions
- Non-uniform sampling methods

Analytical work ahead:

- Investigate quantity of data necessary for accurate jump height
- Statistical analysis for noisy phase data

Other directions:

- Application specific priors
- Comparing with real data
- Corners from edges



Acknowledgements



This work was started over the summer of 2015 as part of ASU's MCTP program. I would like to thank the NSF for their gracious support of the program, and Dr. Kostelich for his dedication in continuing this program at ASU.

I would also like to thank my advisor Dr. Gelb and everyone in our research group for their mentorship:

- Dr. Anne Gelb
- Dr. Douglas Cochran
- Dr. Rodrigo Platte
- Shane Lubold
- Rachel Nahon

