Faculty:
Wu Feng
Atharva Gondhalekar

Multi-dimensional Analysis of Real-time Edge Detection on an Embedded System

By Lucas Weaver

Volunteer Research Position

Motivation

Context: edge detection on peripheral devices have become extremely prominent with the rise in self-driving, especially as Tesla abandoned close-range radar in 2021 and ultrasonic sensors in 2023 in favor of a completely computer-vision based approach[1]

Problem: edge detection strategies need to be accurate, power-efficient as well as act in real time.

Solution: perform a multi-dimensional analysis of the Sobel filter to determine the best parameters for use in self-driving applications by analyzing power consumption, runtime, and accuracy as measured by Pratt's Figure of Merit

Tesla failing crash test [2]

Complexity of driving environment[3]

Approach

Utilize Sobel Filter
- Canonical Standard
- Easily Parallelizable with OpenMP
- Many parameters to compare across for optimal performance

Test on Raspberry Pi Compute Module 5 (RPICM5)
- Realistic edge device for self-driving application
- Readily available
- quad-core 64-bit Arm Cortex-A76 (Armv8) SoC @ 2.4GHz

Evaluate with Berkeley Segmentation Dataset (BSDS300)
- Open-source dataset for segmentation and edge detection
- Human-labeled ground truth images
- Use Pratt FOM[2] to measure accuracy

$$\sqrt{G_x^2 + G_y^2}$$

Euclidean metric

Compare distance metrics and precision
- Euclidean vs Manhattan
- Int vs float vs double

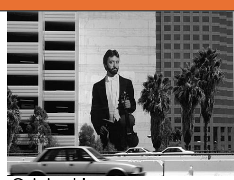
$$|G_x| + |G_y|$$

Manhattan metric

Keep other parameters fixed
- Offset, scale, and threshold will be fixed
- Do not have significant effect on runtime or power

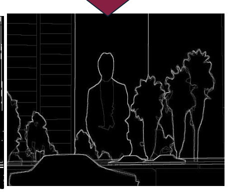
Evaluation

Image from the BSDS300 dataset. 300 Images were segmented manually by human participants, then overlaid to find a "ground truth " segmentation , or ideal edge detection result



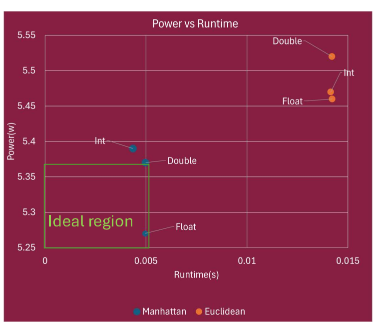
Original Image

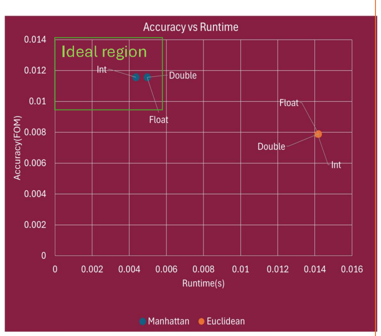
Double-precision Euclidean



Ground Truth

Double-precision Manhattan





Euclidean vs Manhattan accuracy
Null hypothesis H_0: $\mu_1 - \mu_2 = 0$
Alternative hypothesis H_1: $\mu_1 - \mu_2 \neq 0$

T-Value	DF	P-Value
-6.32	1648	0.000

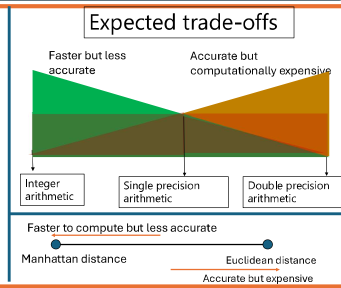
Int vs Float runtime
Null hypothesis H_0: $\mu_1 - \mu_2 = 0$
Alternative hypothesis H_1: $\mu_1 - \mu_2 < 0$

T-Value	DF	P-Value
-65.02	410	0.000

Distance Metric	Precision	Runtime	Accuracy	Power
Manhattan	Int	0.00436	0.01156	5.39
Manhattan	Float	0.00496	0.01156	5.27
Manhattan	Double	0.00498	0.01156	5.37
Euclidean	Int	0.01415	0.00787	5.47
Euclidean	Float	0.01422	0.00787	5.46
Euclidean	Double	0.01421	0.00791	5.52

Discussion

- **Accuracy**
  - Manhattan higher accuracy
  - Precision is negligible
- **Runtime**
  - Manhattan lower runtime
  - Int best runtime
- **Power**
  - Consistently lower power consumption with Manhattan distance vs. Euclidean distance
  - Single-precision arithmetic requires lower power better than other double precision



Conclusion

After running 2 sample T-tests for significance on both the accuracy and runtime of different parameters, we conclude that:

Best Parameters:
- Manhattan distance metric for application of Sobel filter
- Single precision arithmetic
- Provides best balance of power, accuracy and runtime

Importance of empirical testing
- Despite Manhattan being an approximation, it performed better
- Theoretical work should always be verified by empirical testing

Future Work

- Test other edge detectors
  - Scharr, canny, Laplacian, etc,
- Use more modern accuracy metrics for edge detection
- Evaluate power consumption more rigorously
  - Current meter only polls once per second
- Test on images specific to self-driving environments
- Vary number of threads

References

[1]"Tesla Vision Update: Replacing Ultrasonic Sensors with Tesla Vision | Tesla Support," Tesla. Accessed: Apr. 24, 2025. [Online]. Available: https://www.tesla.com/support/transitioning-tesla-vision

[2]F. Lambert, "Tesla Autopilot drives into Wile E Coyotefake road wall in camera vs lidar test," Electrek. Accessed:Apr. 24, 2025. [Online]. Available:https://electrek.co/2025/03/16/tesla-autopilot-drives-into-wall-camera-vs-lidar-test/

[1]

[3]P. L. Liu, "Drivable Space in Autonomous Driving — The Industry," Medium. Accessed: Apr. 24, 2025. [Online]. Available: https://medium.com/@patrickllgc/drivable-space-in-autonomous-driving-the-industry-7a4624b94d41

[4]W. Pratt, Digital Image Processing. New Jersey: John Wiley & Sons, Inc., 2006.