



# Stereo Projection

## Using Primal-Dual Variational Method

Course :: GPU Programming in Computer Vision (WS2013/14)

Team :: *Warp64* (group 9)

Adviser :: Mohamed S.

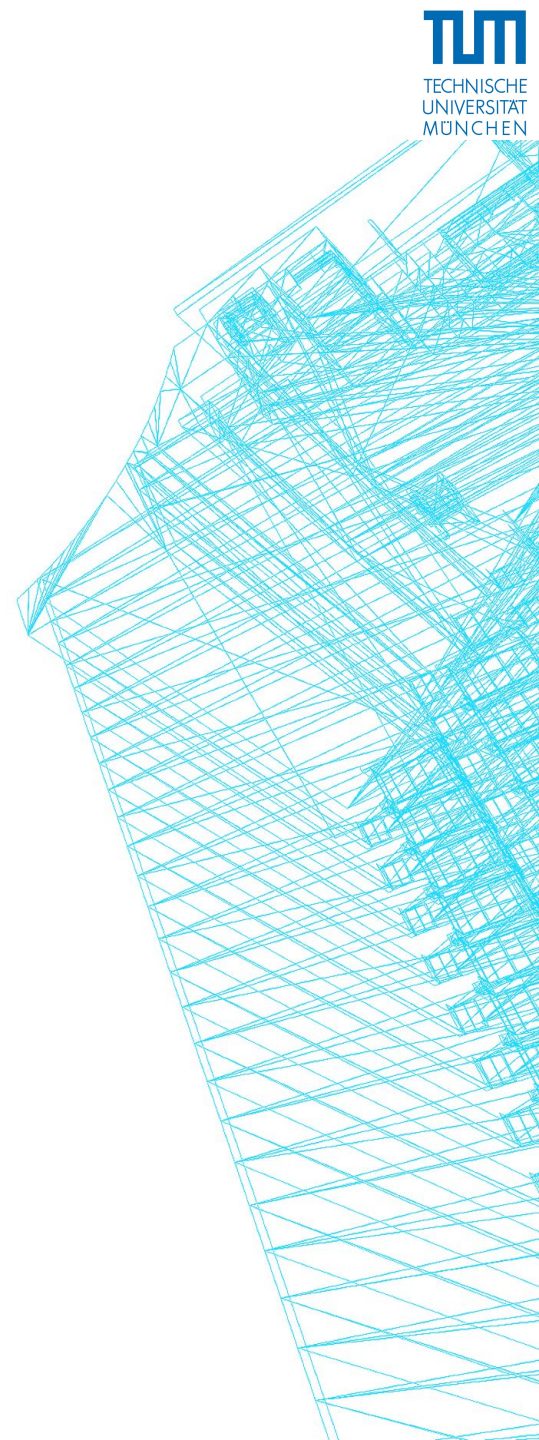
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*"You must be the change you wish to see in the world." — Mahatma Gandhi*



# Introduction

*".. You can't connect the dots looking forward; you can only connect them looking backwards.." — Steve Jobs*





# Aim

- Implementation of a Computer Vision algorithm with the goal focused on performance measure and comparing memory types.
- And a little bit of theory..





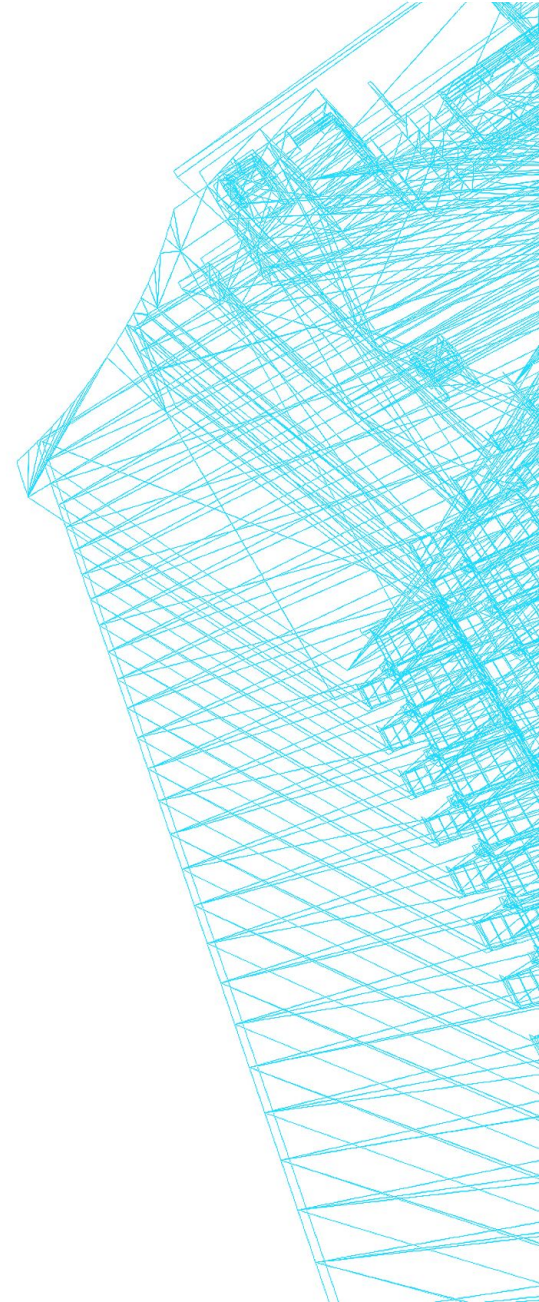
# Contents

- Stereo Projection
  - Example
  - Theory
  - Implementation
  - Result and Performance
  - GUI and Demo



# EXAMPLES

*"We are apt to forget that children watch examples better than they listen to preaching." — Roy L. Smith*



# Example 1: STATUE IMAGE



Left Image



Depth image



Right Image



## Example 2: Man Image



Left Image



Depth image

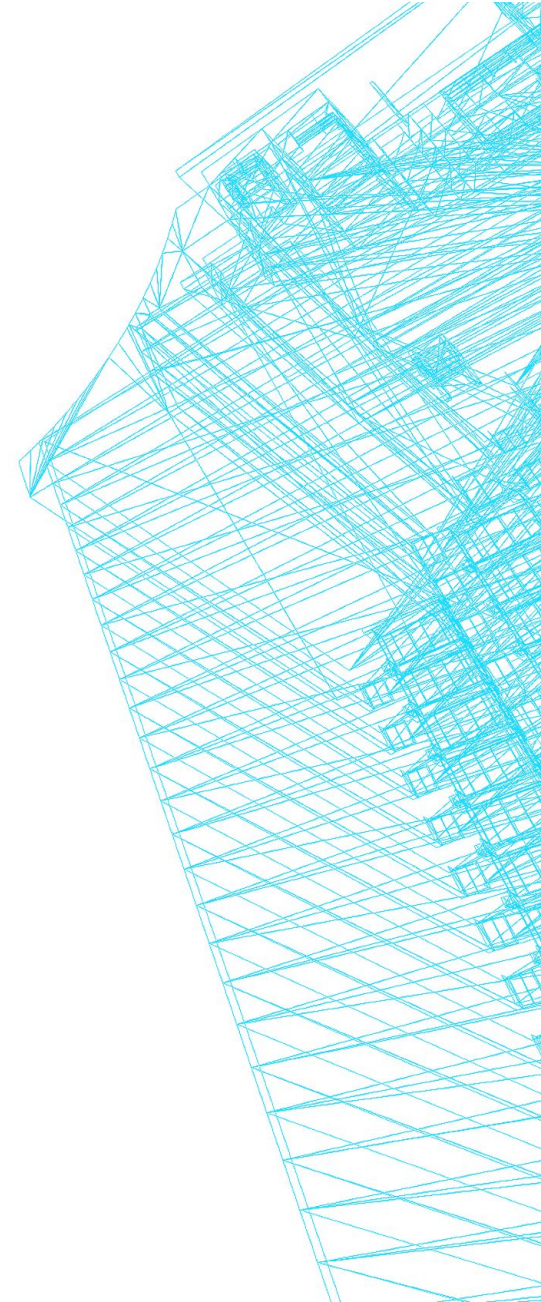


Right Image



# THEORY

*"If the facts don't fit the theory, change the facts." — Albert Einstein*





# Formulation: Variational Method

- Energy Equation in terms of disparity

$$\min \left\{ \underbrace{\int_{\Omega} |\nabla u(x)| dx}_{\text{Regularizer}} + \underbrace{\int_{\Omega} \rho(u(x), I_l, I_r)}_{\text{Data Term}} \right\}$$

- Regularizer – Smoothness in the disparity values of the neighboring pixels.
- Data Term – Stereo image matching for the given disparity level.

# Primal Dual Formulation

- Introduce Dual variable  $\varphi$  (3D vector), acts as a diffusion operator of the depth map  $v$ .

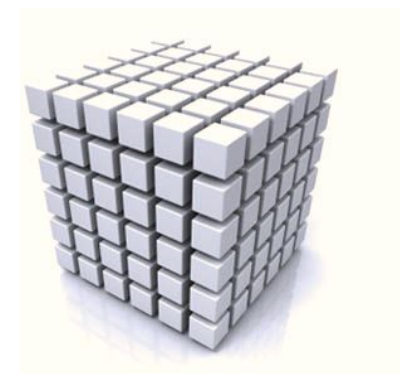
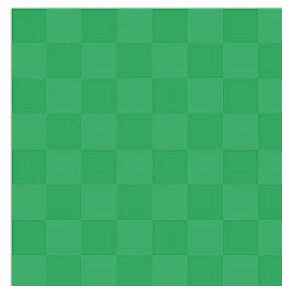
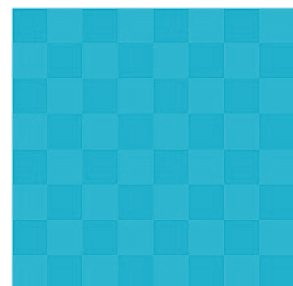
$$\min_v \{ \max_{\varphi} \{ \int_{\Sigma} \nabla_3 v \cdot \varphi \} \}$$

- Primal Dual Update steps

$$\begin{aligned} (\varphi^h)^{n+1} &= proj_k ((\varphi^h)^n + \sigma(\nabla v^n)) \\ (v^h)^{n+1} &= proj_c ((v^h)^n + \tau(div(\varphi^h)^{n+1})) \\ (\bar{v}^h)^n &= 2(v^h)^{n+1} - (v^h)^n \end{aligned}$$

- Projection operator implies mapping of the dual and primal variables on the respective subspaces.

# FORMULATION: VISUALISATION



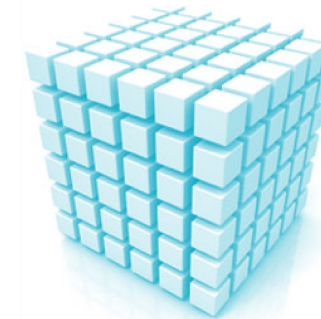
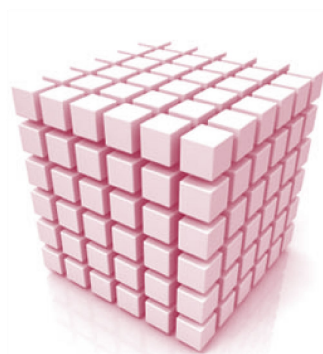
	Left Image, $I_{\text{left}}$	Right Image, $I_{\text{right}}$	Data Term, $g$																
Dimensions	$w \times h$	$w \times h$	$w \times h \times s$																
Value of a cell	$[0, 1]$	$[0, 1]$	$R$																
Calculation	$\langle \text{input} \rangle$	$\langle \text{input} \rangle$	<table> <tr> <th></th><th>Left Image, <math>I_{\text{left}}</math></th><th>Right Image, <math>I_{\text{right}}</math></th><th>Data Term, <math>g</math></th></tr> <tr> <td>Dimensions</td><td><math>w \times h</math></td><td><math>w \times h</math></td><td><math>w \times h \times s</math></td></tr> <tr> <td>Value of a cell</td><td><math>[0, 1]</math></td><td><math>[0, 1]</math></td><td><math>R</math></td></tr> <tr> <td>Calculation</td><td><math>\langle \text{input} \rangle</math></td><td><math>\langle \text{input} \rangle</math></td><td><math>g(i, j, k) = \mu(I_{\text{right}}(i, j) - I_{\text{left}}(i + k, j))</math></td></tr> </table>		Left Image, $I_{\text{left}}$	Right Image, $I_{\text{right}}$	Data Term, $g$	Dimensions	$w \times h$	$w \times h$	$w \times h \times s$	Value of a cell	$[0, 1]$	$[0, 1]$	$R$	Calculation	$\langle \text{input} \rangle$	$\langle \text{input} \rangle$	$g(i, j, k) = \mu(I_{\text{right}}(i, j) - I_{\text{left}}(i + k, j))$
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where  $s$  = slice depth

initialization



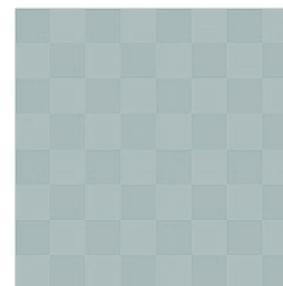
# FORMULATION: VISUALISATION



	Dual, $\Phi$			Primal, $v$			Extrapolation, $\tilde{v}$		
Dimensions	$w \times h \times s$			$w \times h \times s$			$w \times h \times s$		
Value of a cell	$\mathbb{R}^3$			$[0, 1]$			$[-1, 2]$		
Calculation	<div> <div>Dimensions</div> <div>Value of a cell</div> <div>Calculation</div> </div>	<div> <div>Dimensions</div> <div>Value of a cell</div> <div>Calculation</div> </div>	<div> <div>Dimensions</div> <div>Value of a cell</div> <div>Calculation</div> </div>	<div> <div>Dimensions</div> <div>Value of a cell</div> <div>Calculation</div> </div>	<div> <div>Dimensions</div> <div>Value of a cell</div> <div>Calculation</div> </div>	<div> <div>Dimensions</div> <div>Value of a cell</div> <div>Calculation</div> </div>	<div> <div>Dimensions</div> <div>Value of a cell</div> <div>Calculation</div> </div>	<div> <div>Dimensions</div> <div>Value of a cell</div> <div>Calculation</div> </div>	<div> <div>Dimensions</div> <div>Value of a cell</div> <div>Calculation</div> </div>

until convergence

# FORMULATION: VISUALISATION

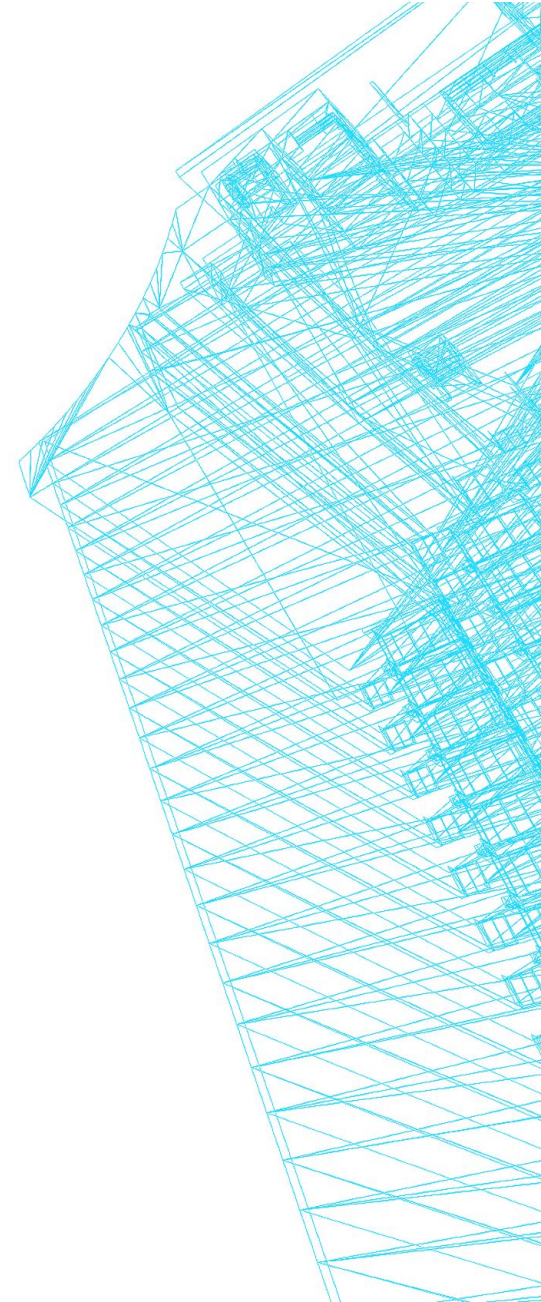


	Depth Map, d	
Dimensions	w x h	
Value of a cell	[0, 255]	
Calculation		Depth Map, d
	Dimensions	w x h
	Value of a cell	[0, 255]
	Calculation	$g(i, j) = \sum_{k=0}^s v_{n+1}(i, j, k)$



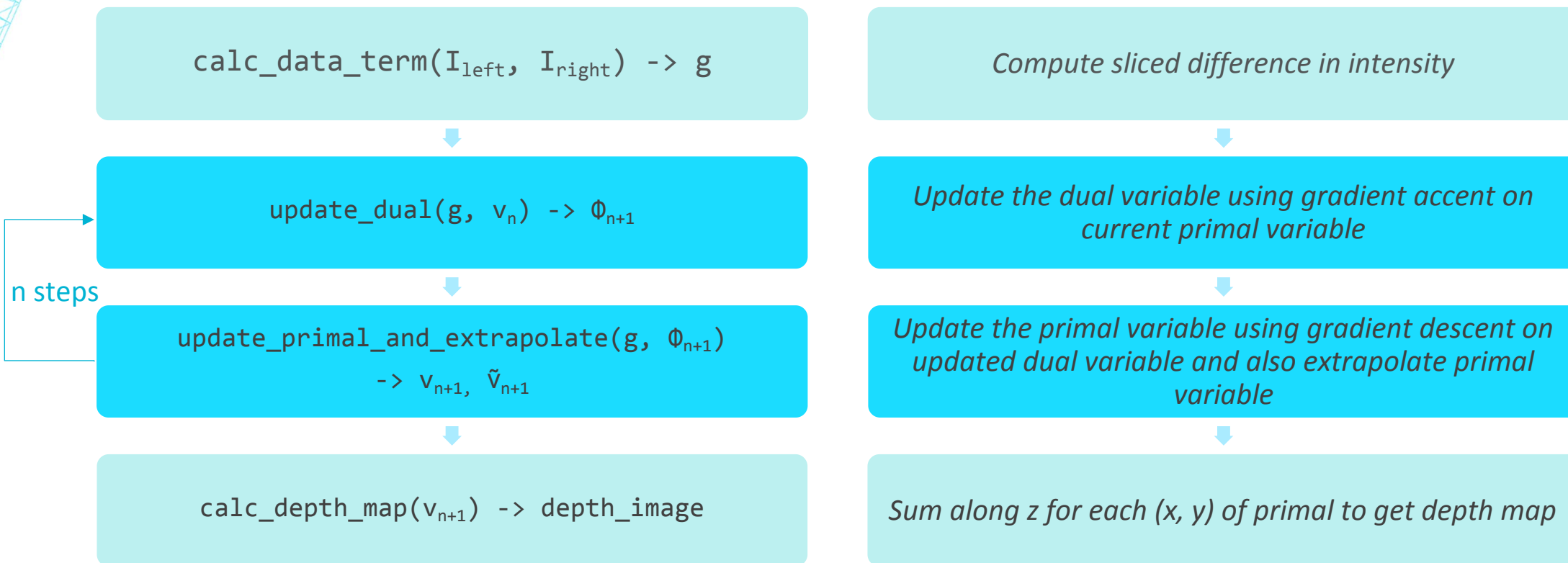
# Implementation

*"A good idea is about ten percent and implementation and hard work, and luck is 90 percent." — Guy Kawasaki*

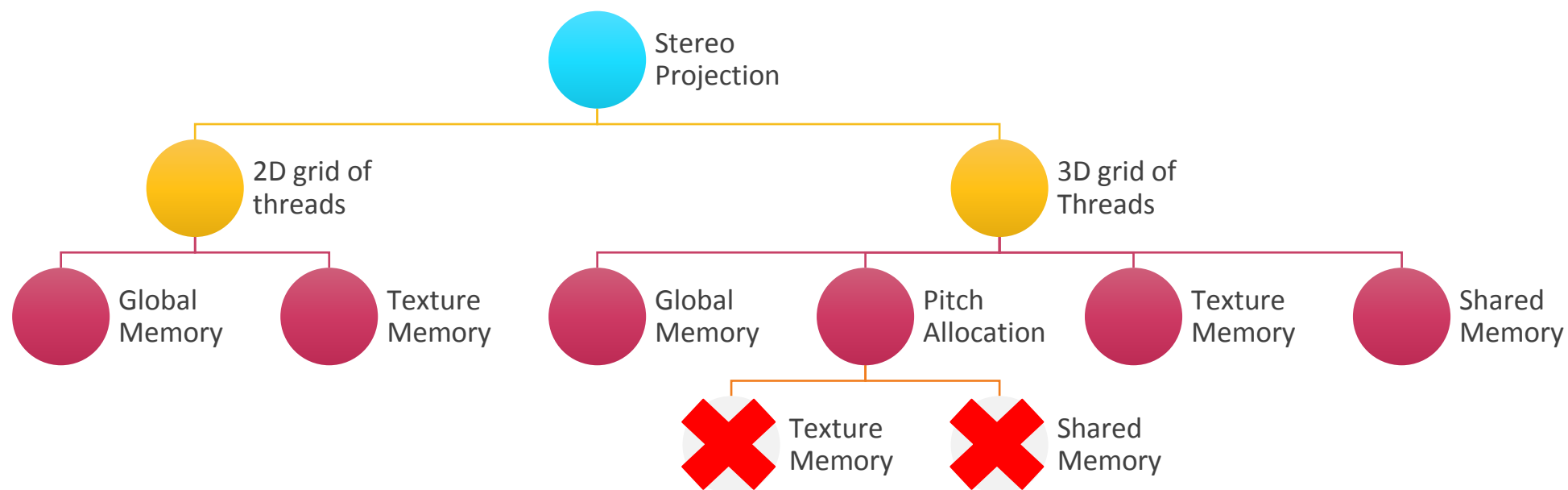




# IMPLEMENTATION: Kernels



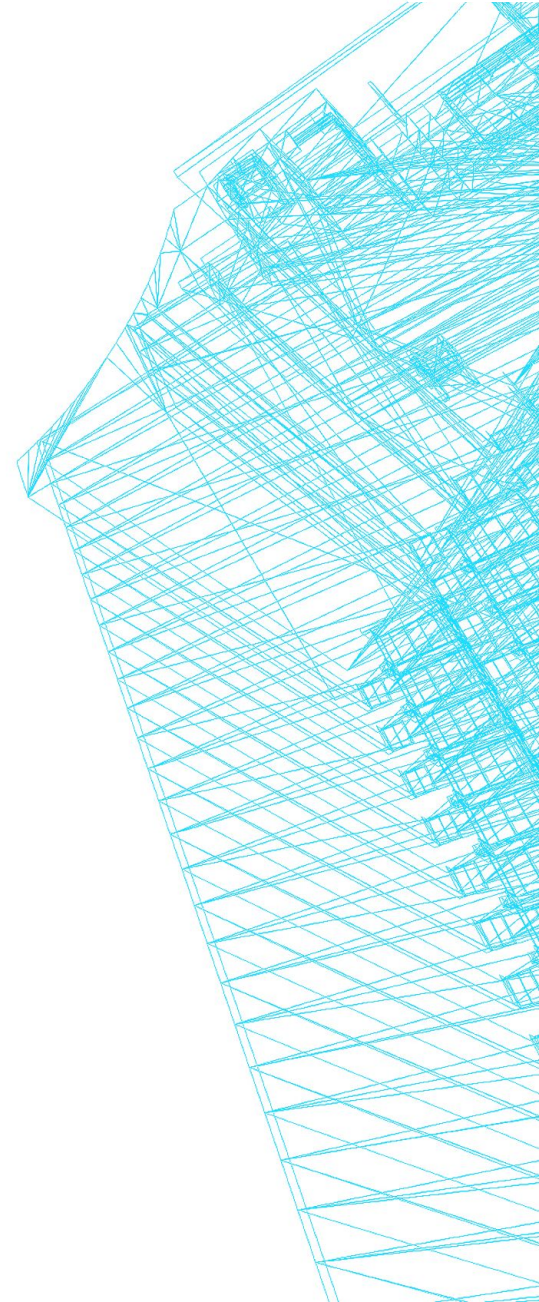
# Implementation: GPU Techniques





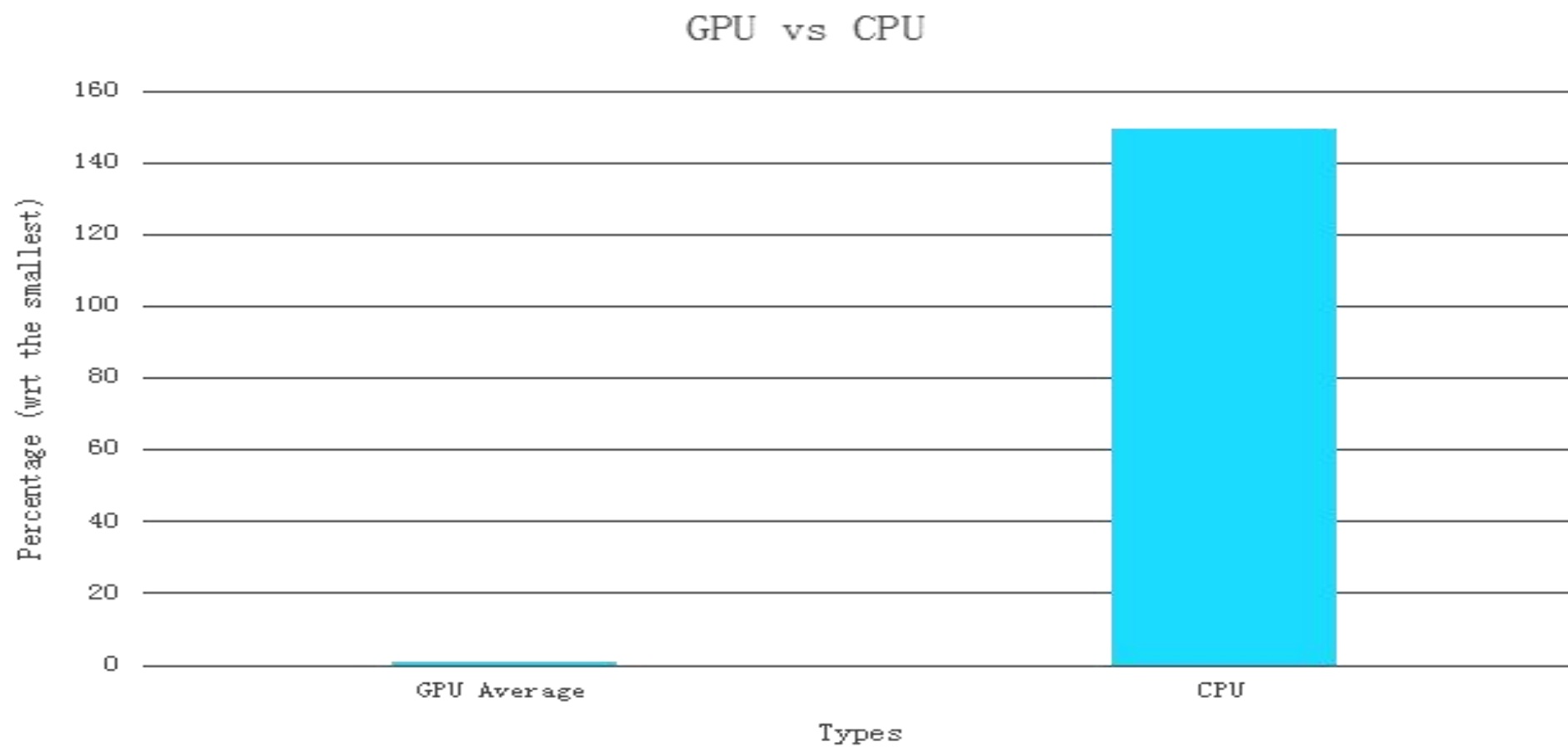
# RESULTS and performance

*"Insanity: doing the same thing over and over again and expecting different results." — Albert Einstein*

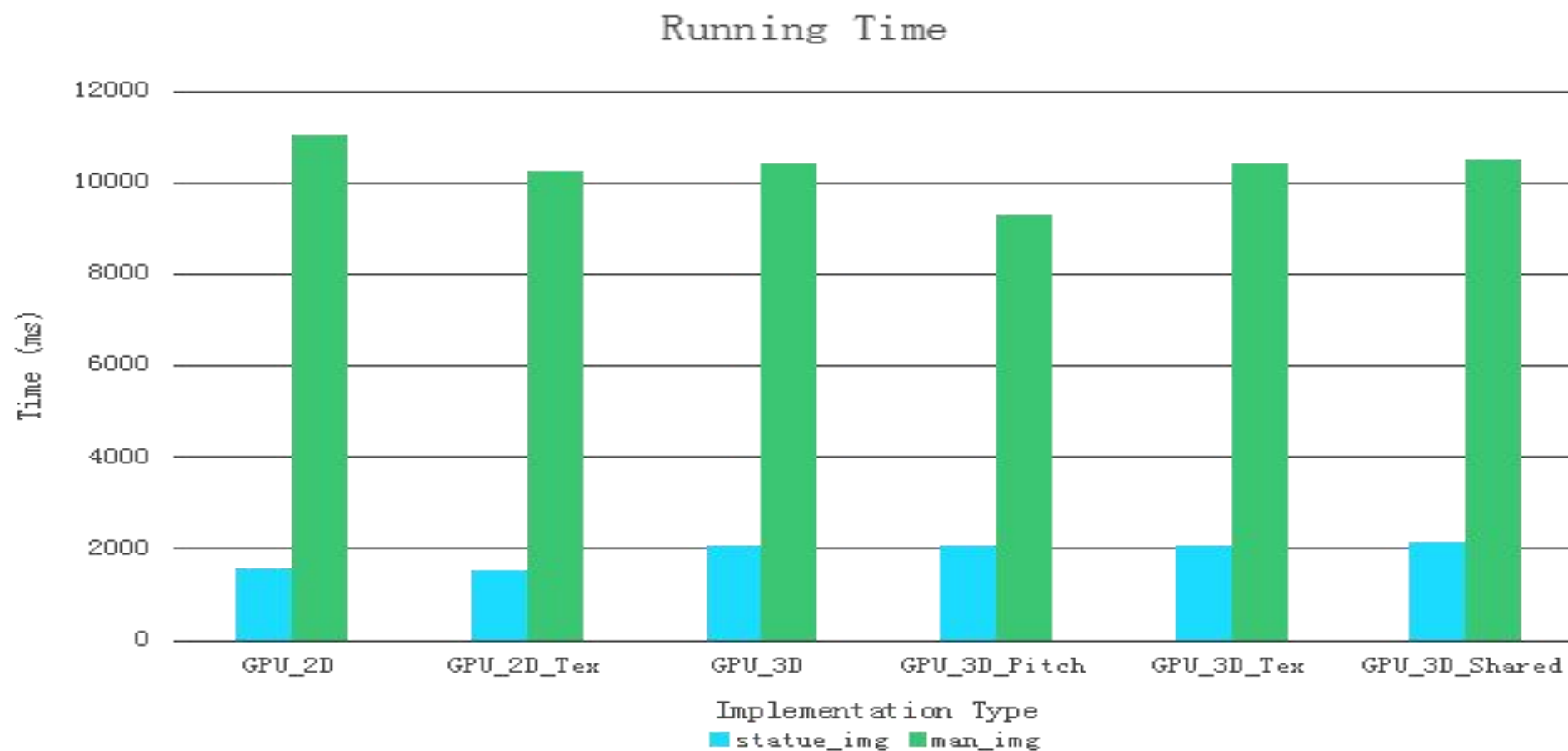


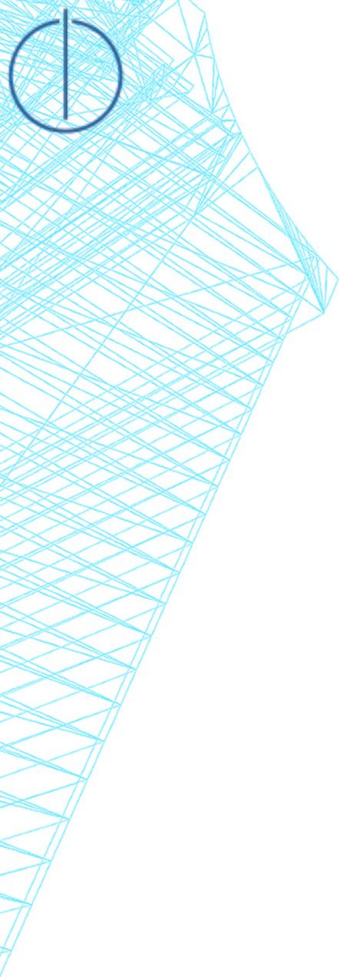


# RESULTS: GPU v/s CPU

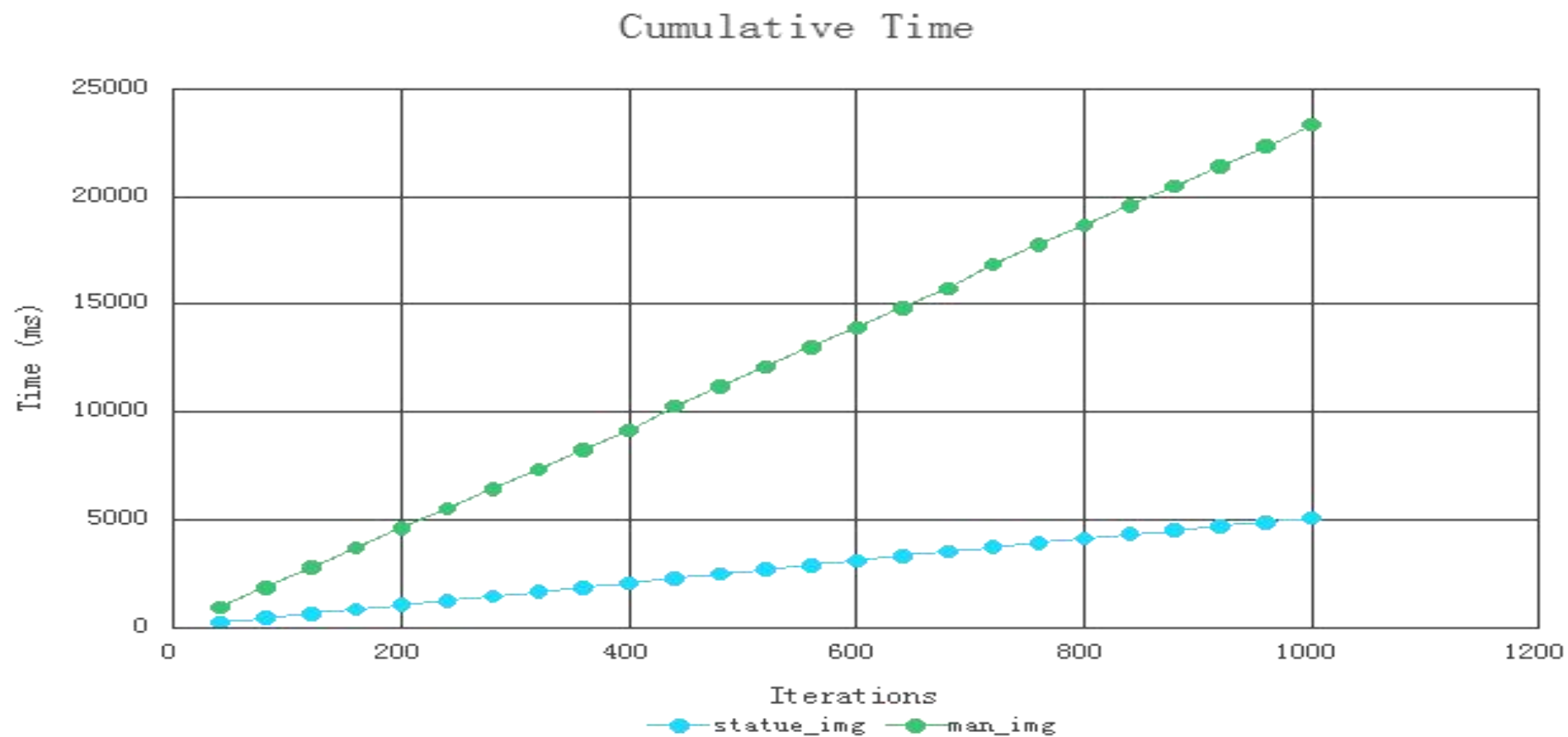


# RESULTS: RUN TIME RESULTS



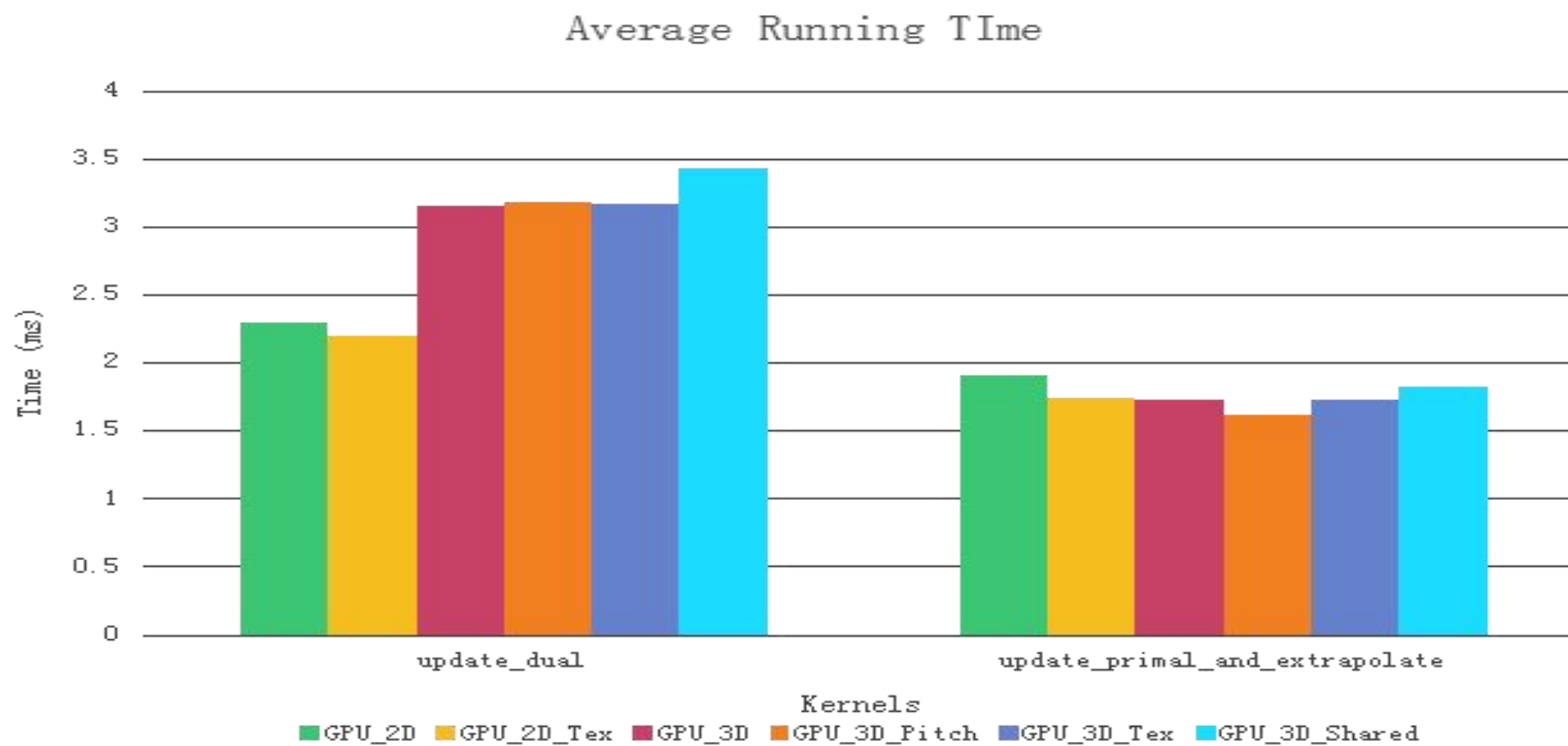


# Results: CONVERGENCE



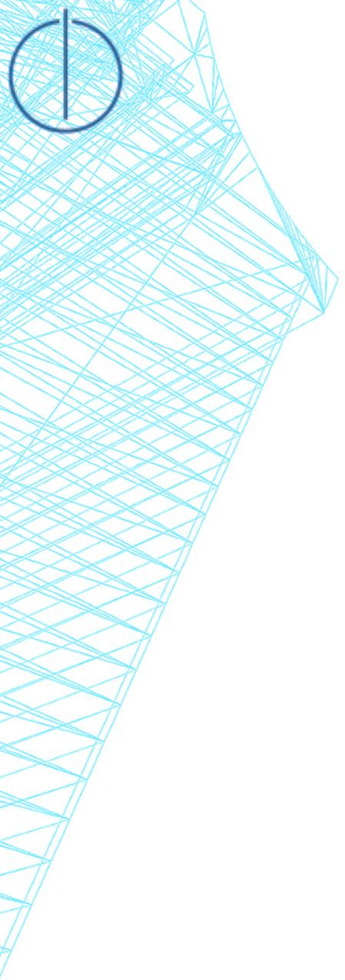


# RESULTS: KERNEL AVERAGE RUNTIME

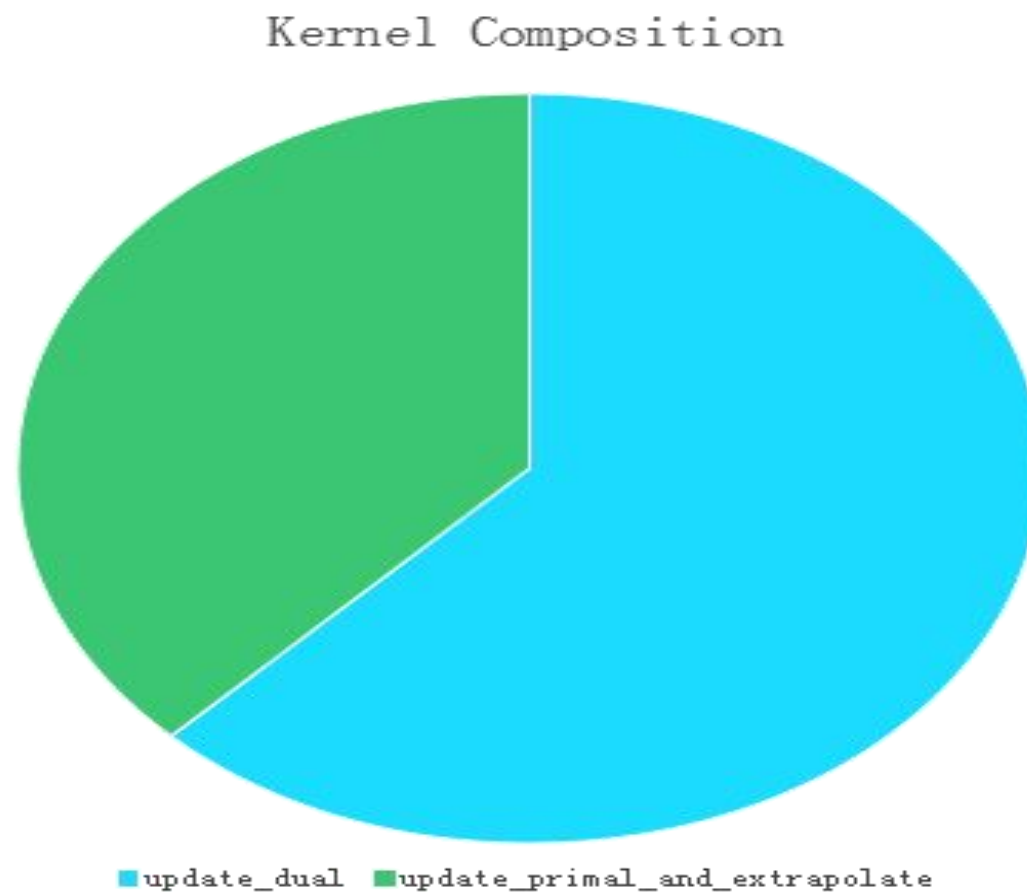


# RESULTS: TYPES COMPARISONS

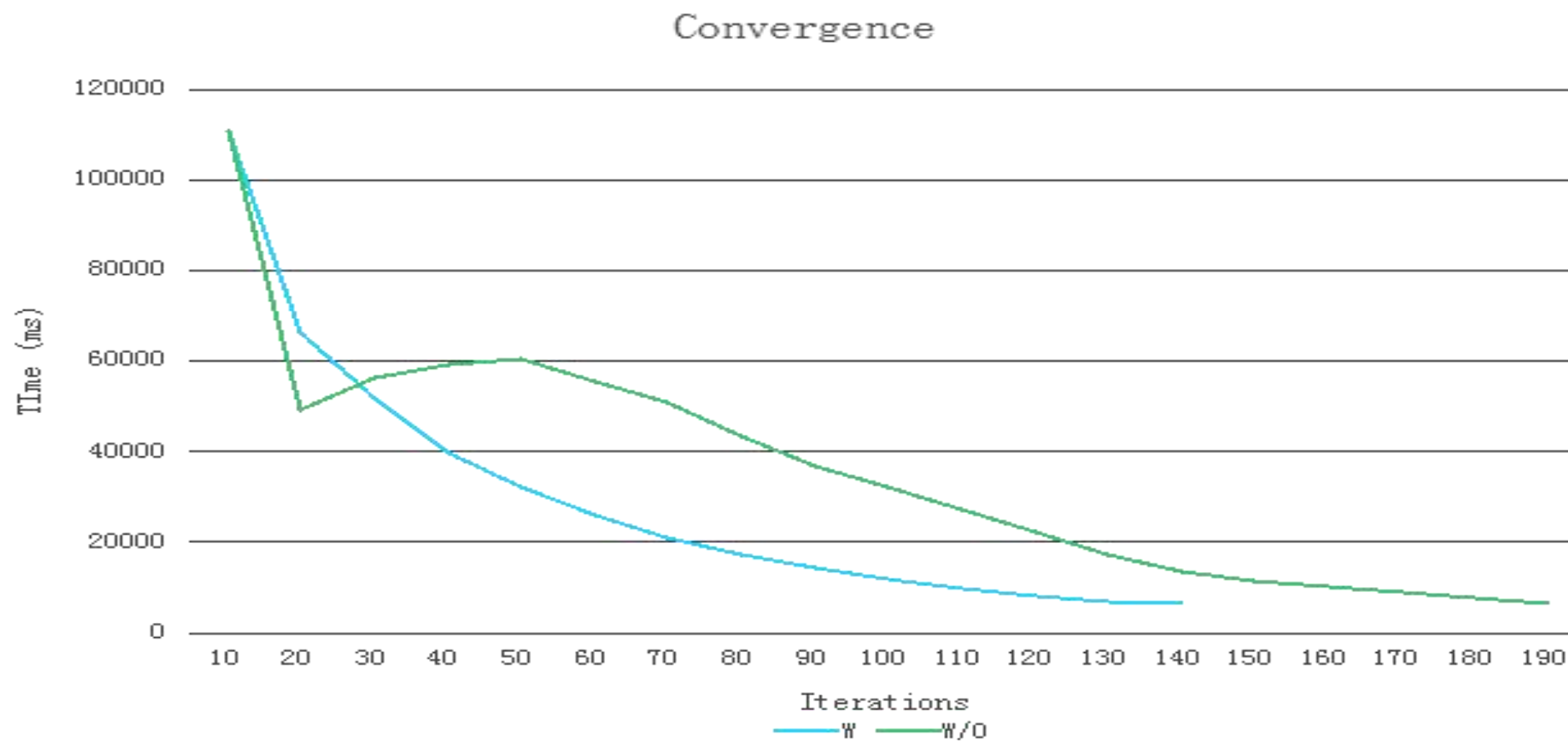




# Results: COMPOSITION OF KERNELS



# Results: CONVERGENCE (HACK)

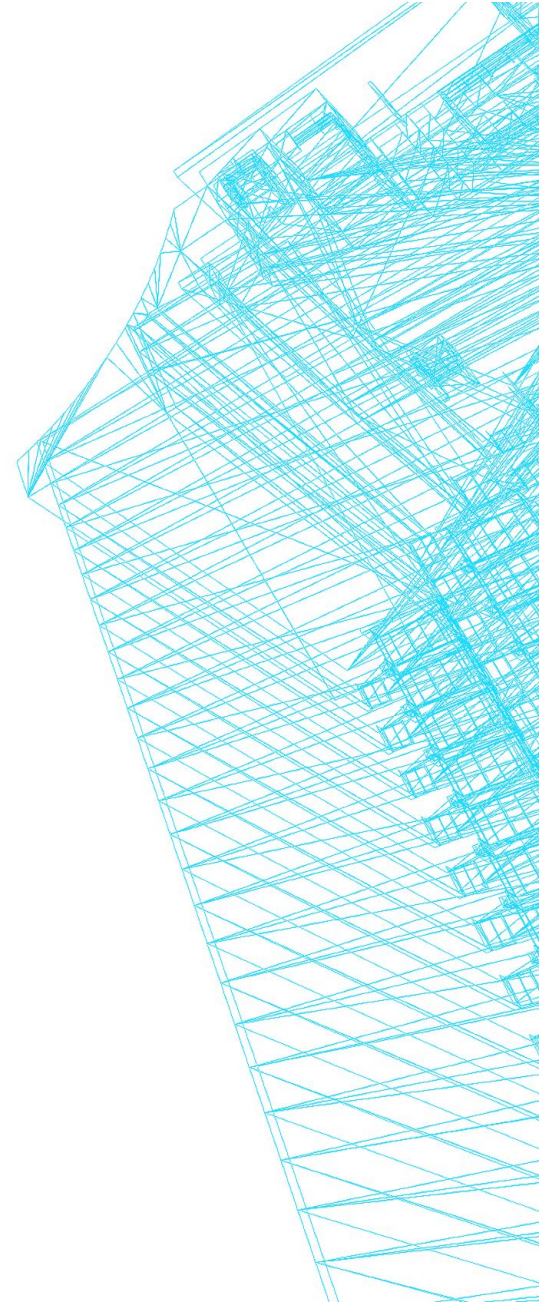






# GUI and DEMO

*“What is it indeed that gives us the feeling of elegance in a solution, in a demonstration?” — Henri Poincaré*



# To Sum Up

- Great performance boost compared to CPU.
- We have seen different types of GPU techniques.
- In cc  $\geq 2.x$ , texture does not give a big boost.
- Pitch allocation always improves performance (except for already pitched memory).
- Shared Memory is useful in case of  $O(n^2)$  access.
- In convex problems, initialization hacks may lead to faster convergence.



# References

[1] Pock T., Cremers D., Bischof H., Chambolle A., *Global Solutions of Variational Models with Convex Regularization*

[2] Variational Methods, TUM Class Lectures

[3] CUDA Programming GUIDE

