



# SceneNet: 3D Reconstruction of Videos Taken by the Crowd on GPU

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GTC 2015 – San Jose



# SagivTech Snapshot

- Established in 2009 and headquartered in Israel
- Core domain expertise: GPU Computing and Computer Vision
- What we do:
  - Technology
  - Solutions
  - Projects
  - EU Research
  - Training
- GPU expertise:
  - Hard core optimizations
  - Efficient streaming for single or multiple GPU systems
  - Mobile GPUs



# Mobile Crowdsourcing Video Scene Reconstruction



- If you've been to a concert recently, you've probably seen how many people take videos of the event with mobile phone cameras



- Each user has only one video – taken from one angle and location and of only moderate quality



# The Idea behind SceneNet

Leverage the **power of** multiple mobile phone cameras  
to create a **high-quality 3D** video experience that is  
**sharable** via social networks



# SceneNet as a FET SME collaborative project

Uni Bremen

EPFL



SCiLS

ERS

SagivTech



# SceneNet Advisory Board



Prof. Dr. Franziska Boehm  
Uni. Munster



Mr. Malte Blumenthal  
Eventim

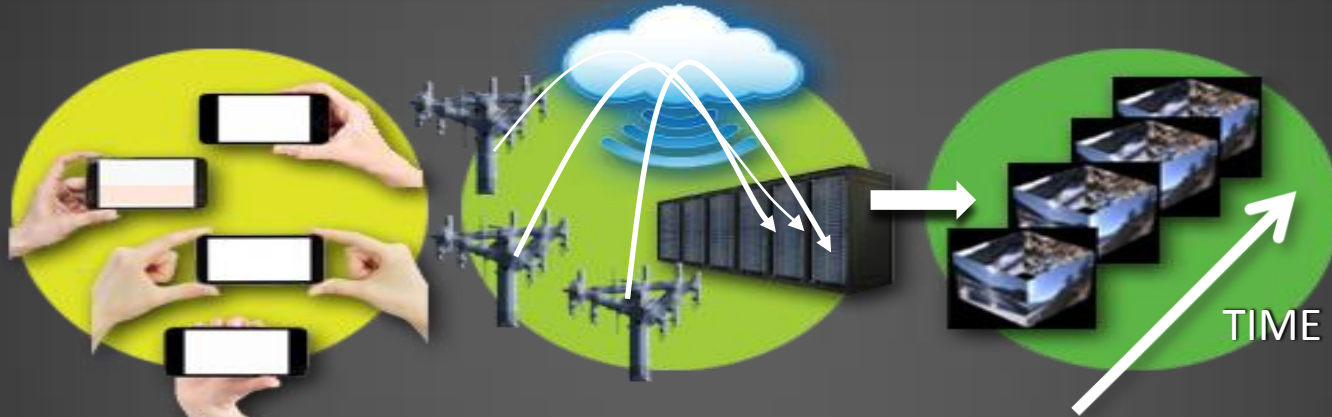


Prof. Dr. Hans-Georg Stark  
Hochschule Aschaffenburg



Mr. Izhar Ashdot  
Musician

# Creation of the 3D Video Sequence



The scene is photographed by several people using their cell phone camera

The video data is transmitted via the cellular network to a High Performance Computing server.

Following time synchronization, resolution normalization and spatial registration, the several videos are merged into a 3-D video cube.

# The Event Community



A 3-D video event is created.

The 3-D video event will be available on the internet as public or private event.

The event will create a community, where each member may provide another piece of the puzzle and view the entire information.



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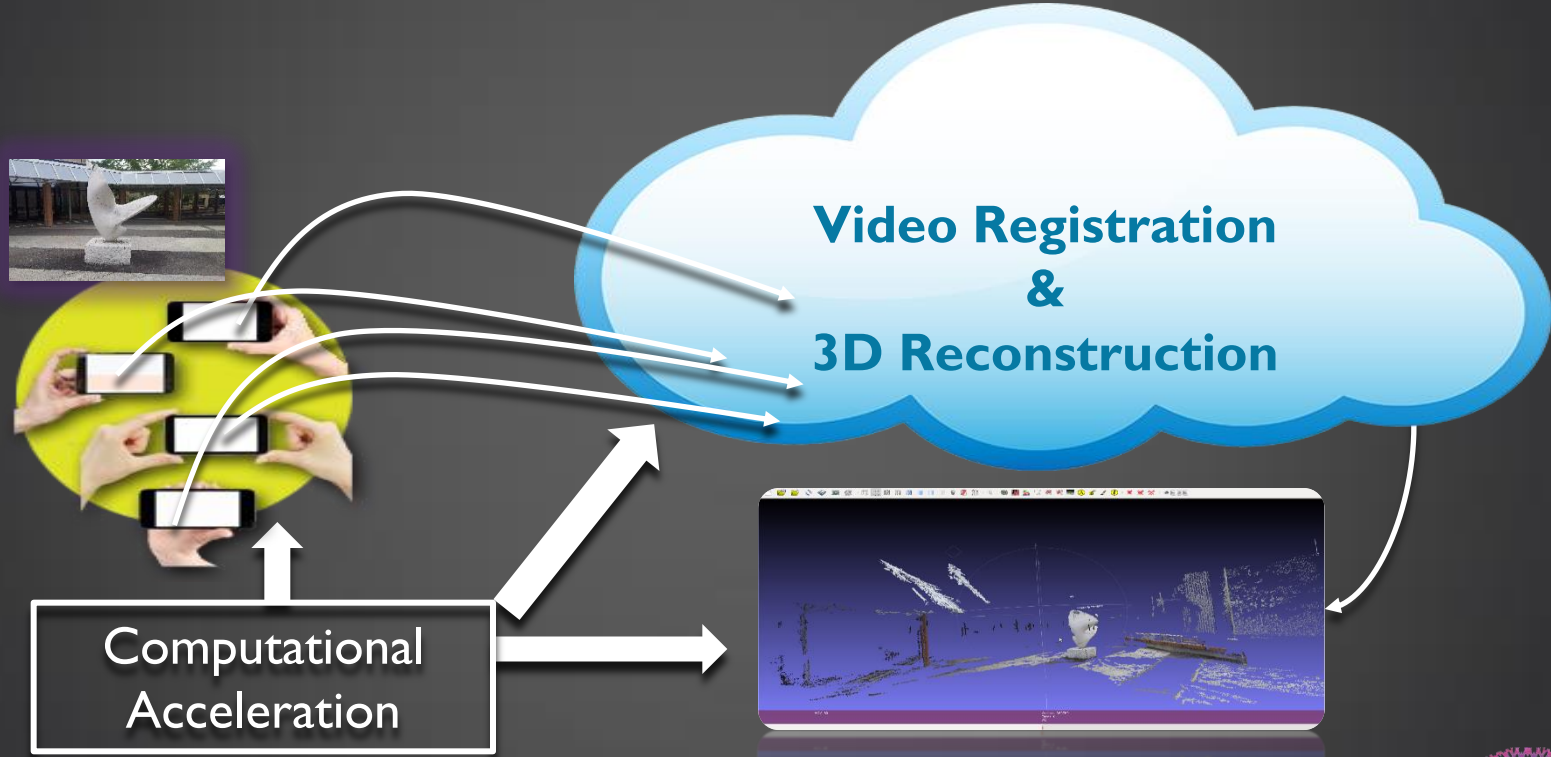
The event will create a community, where each member may provide another piece of the puzzle and view the entire information.

SCENE  
NET

# The Combined Model: Mobile & Cloud Computing



# GPU Computing in SceneNet



# Motivation for Computational acceleration in SceneNet - on the device

- The mobile device performs several tasks for SceneNet alongside its usual tasks (calls, graphics etc.)
- Pre processing algorithms run at  $< 1$  frame per second on the CPU of the mobile device
- Need significant speedup !
- Hence, GPU to the rescue !

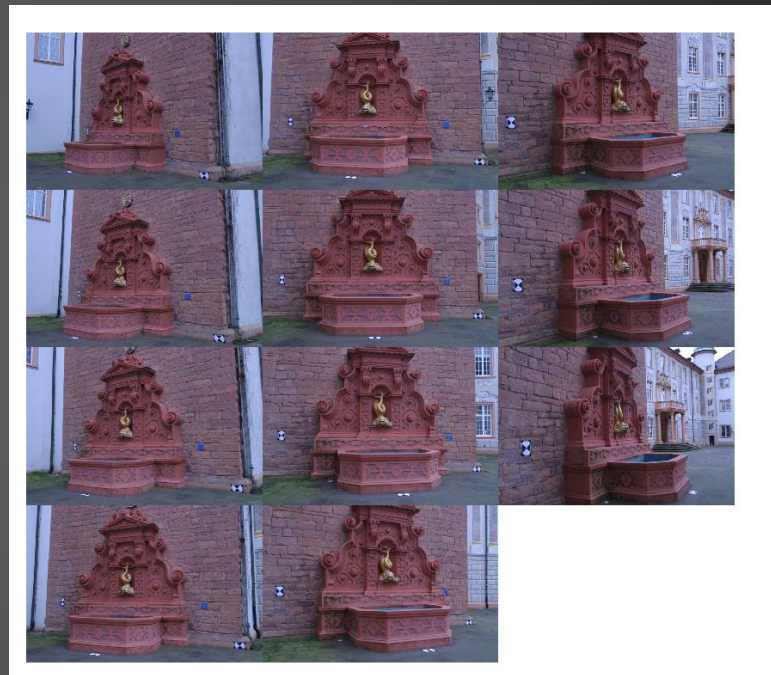
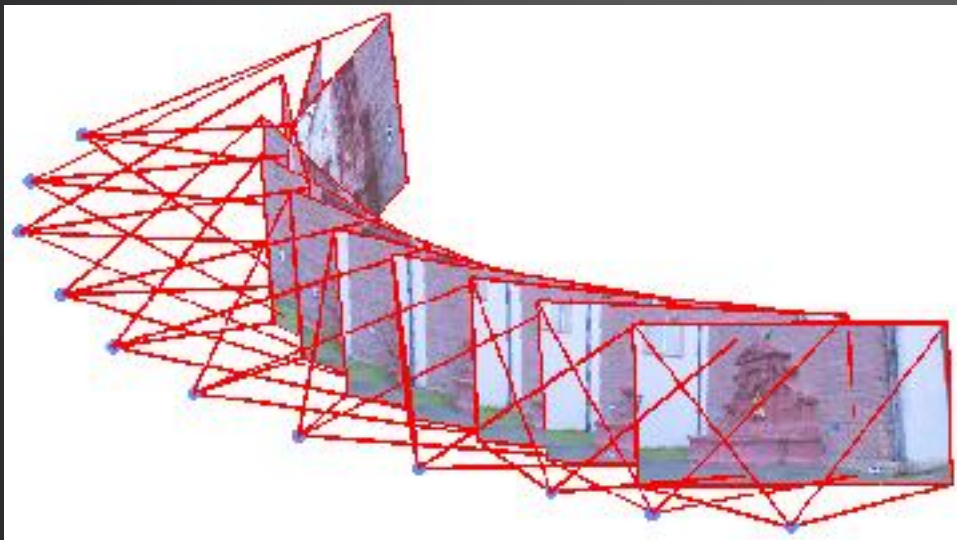
# Convolution Acceleration on Tegra K1

Image Size	CPU Gold	1 CPU Thread	4 CPU Threads	GPU	Speedup
1024 x 1024	142	18	10.2	4	X2.6
2048 x 2048	740	100	50	9	X5.5

# Motivation for Computational acceleration in SceneNet - on the server

- The server related tasks are mainly video synchronization and registration and 3D reconstruction
- Currently, the compute power does not allow for near real time implementations
- **Solution: GPU acceleration is an enabler for the server based operations**
- This relies on SagivTech Background IP Infrastructure where we accommodate it to the needs of SceneNet

# Spatial Calibration





Feature detection +  
Matching

Fundamental matrix  
estimation

Global registration



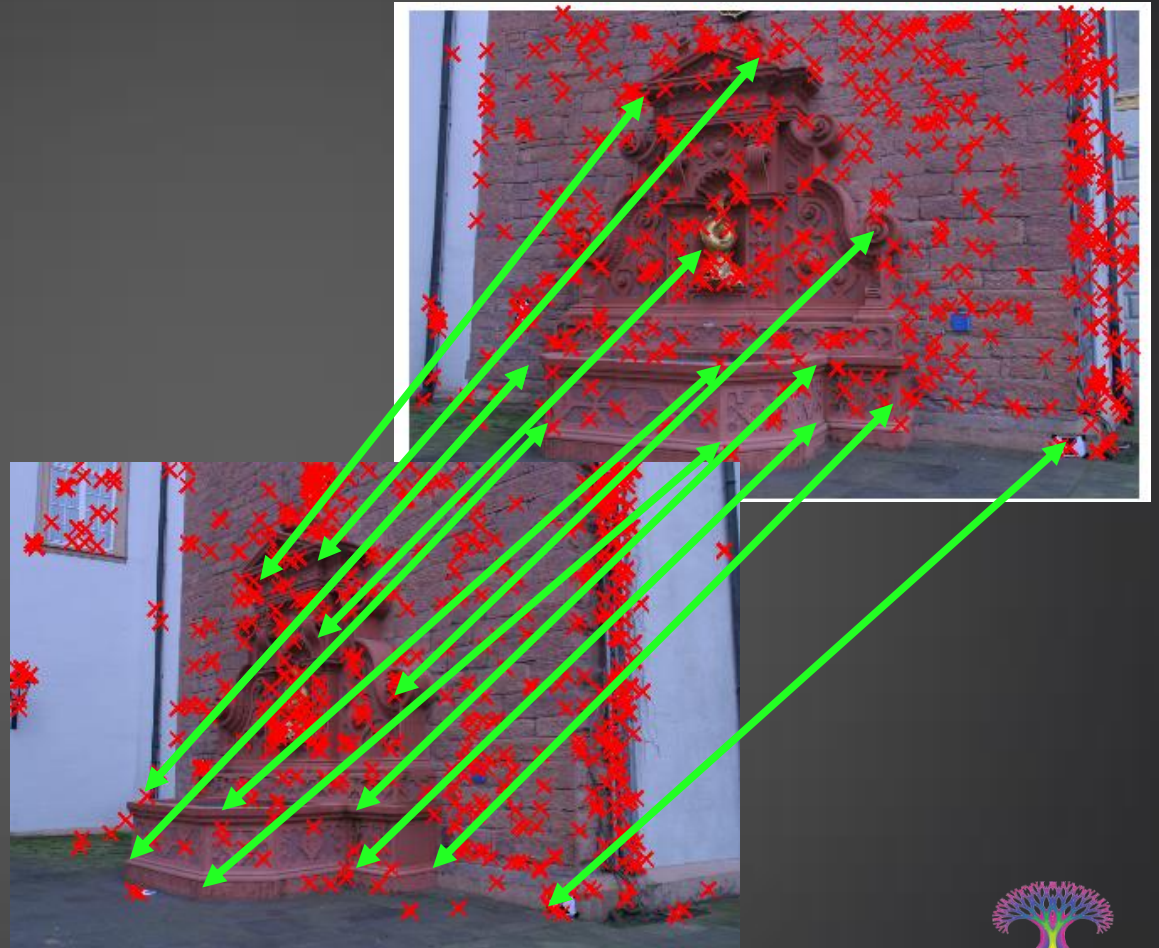
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Feature detection +  
Matching

Fundamental matrix  
estimation

Global registration

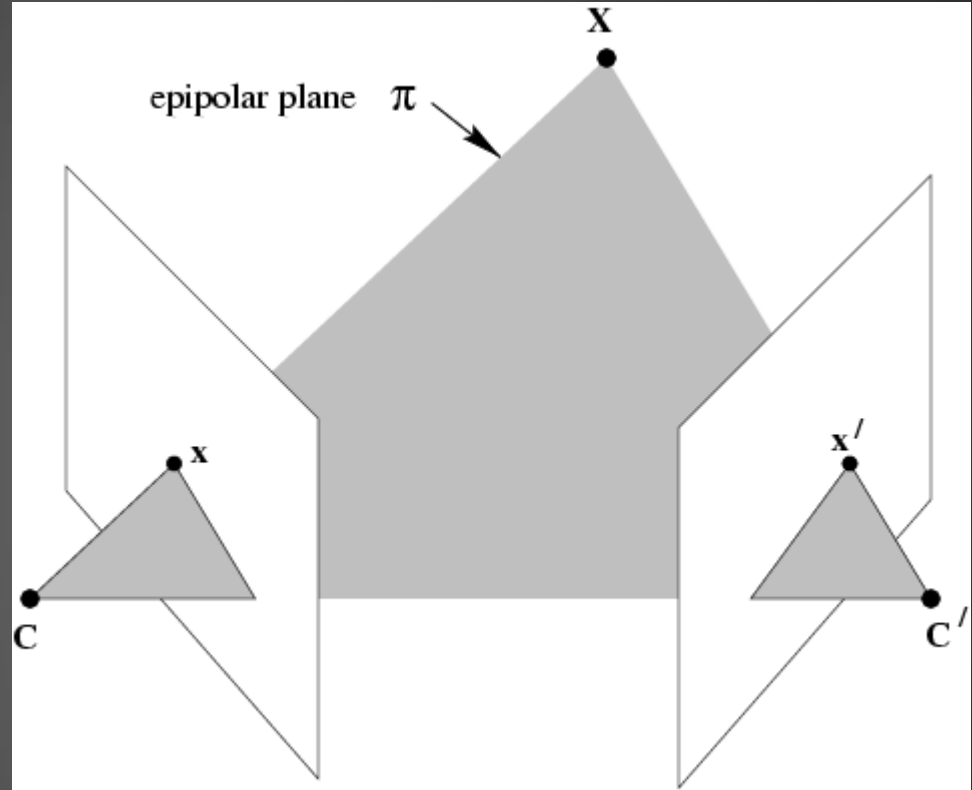


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Feature detection +  
Matching

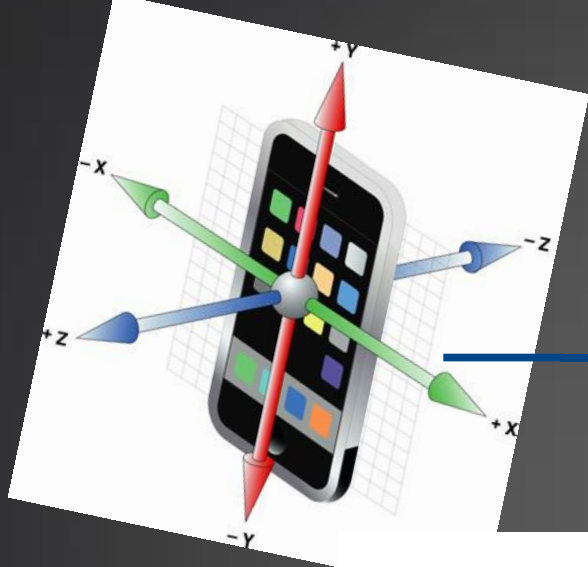
Fundamental matrix  
estimation

Global registration

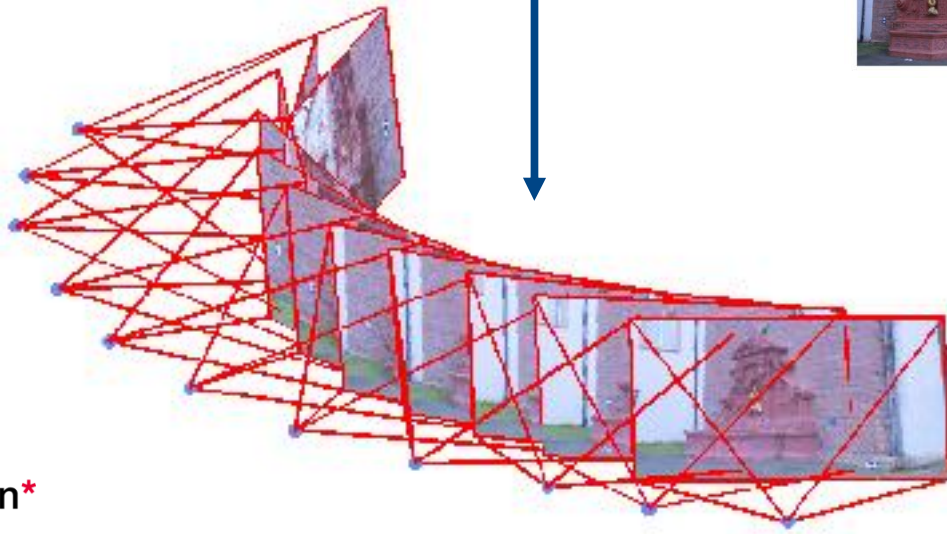
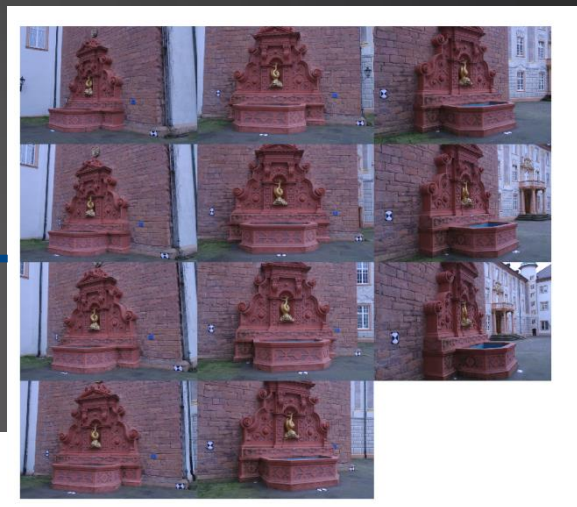


$$\mathbf{x}'^T F \mathbf{x} = 0$$

$$F \in \mathbb{R}^{3 \times 3}$$



Spatial  
Calibration



# Time & Audio Synchronization





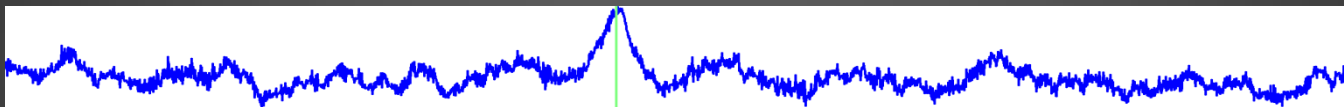
# 3D model reconstruction

- Precise : epipolar matching is both fast and accurate
  - Dense multi-scale description of the images using binary descriptors

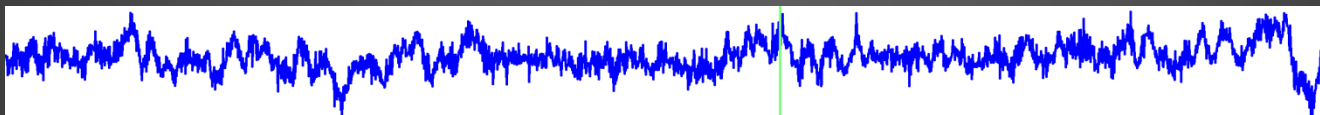


# 3D model reconstruction

- Precise : epipolar matching is both fast and accurate
  - Empirical probability density check to discard false positives at occlusion points



Correct match : max peak above other local max



Wrong match : max peak similar to other local max

# 3D model reconstruction

- Robust : works even with a minimal set of inputs
  - two viewpoints already sufficient for dense reconstruction
  - very few erroneous points



3D reconstruction



# 3D model reconstruction

- Parallelizable : designed with GPU acceleration in mind
  - The algorithm can be parallelized at multiple levels
    - Local operations :
      - Dense description
      - Epipolar matching
      - Triangulation
    - Semi-local operation :
      - Probability density consistency check
    - Multi-view fusing : parallel instead of iterative method

**Computational power bounded by a huge number of small independant tasks**

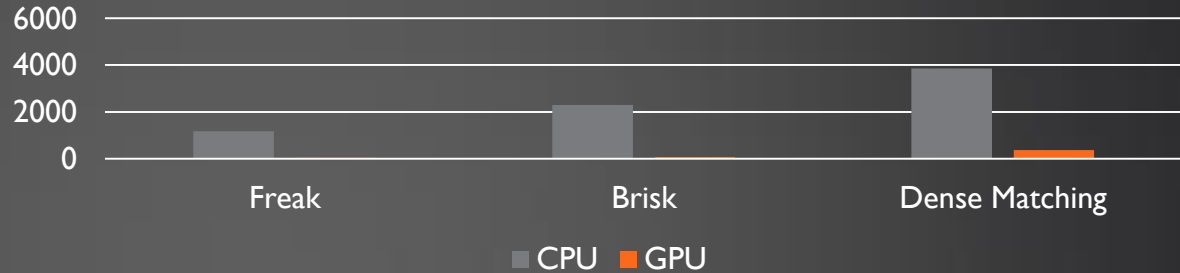


# 3D model reconstruction

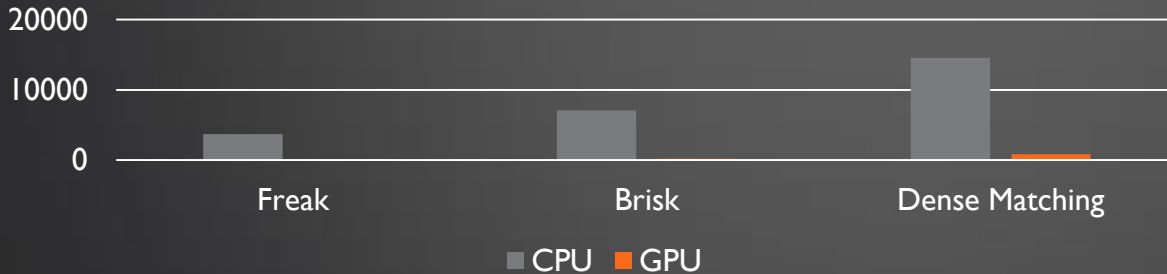
- Impressive performance boosts when migrated to a NVIDIA K20Xm discrete card
- Overall performance speedup is from x5.8 to x7.4 depending on the quality parameter
- Percentage of time used by the CPU when running the GPU code, varies from 40% to 51%
- Freak/Brisk on GPU speedup shows about a x35 factor
- Further optimizations could be applied in the future

# 3D model reconstruction

Quality Param = 0.5



Quality Param = 0.7





# Main Attributes of SagivTech's Streaming Infrastructure

- **Pipelining:** hides memory transfer overhead between CPU and GPU
- **Asynchronous work:** allows job launch on multiple GPUs without waiting for one GPU to finish
- **Peer-to-peer communication:** enables transfer of data between multiple GPUs within the same system


# ST MultiGPU Real World Use Case

SagivTech Multi-GPU Demo


Source Window:  Result Window: 

Configuration

Demo Mode: TV Full Screen Epsilon: 0.5 Lambda: 0.1  
Active GPUs: 1 Filter Video Inner Loops: 20 Outer Loops: 8  
Pipe Size: 1 Pause Normal Noise Apply



GPU Utilization %		Global Stats	
GPU1: 69	GPU2: 0	FPS: 4.25	Scaling (1,1): 1.00
GPU3: 0	GPU4: 0	GFlops: 574.7	Latency: 189.38





One GPU  
One pipe  
Utilization: ~70%

- FPS: 4.25
- Scaling: 1.00
- Note the gaps in the profiler


# ST MultiGPU Real World Use Case

SagivTech Multi-GPU Demo


Source Window:  Result Window: 

Configuration

Demo Mode: TV Full Screen Epsilon: 0.5 Lambda: 0.1  
Active GPUs: 1 Fit Video Inner Loops: 20 Outer Loops: 8  
Pipe Size: 4 Pause Normal Noise Apply



GPU Utilization %		Global Stats	
GPU1: 98	GPU2: 0	FPS: 5.41	Scaling (1,4): 1.00
GPU3: 0	GPU4: 0	GFlops: 730.9	Latency: 517.95



One GPU



4 pipes

Utilization: 95%

- FPS: 5.41
- Scaling: 1.27
- Better utilization using pipes

# ST MultiGPU Real World Use Case

SagivTech Multi-GPU Demo


Source Window:  Result Window: 

Configuration

Demo Mode: TV Full Screen  
Active GPUs: 4  
Pipe Size: 4  
Epsilon: 0.5 Lambda: 0.1  
Inner Loops: 20 Outer Loops: 8  
Normal Noise  
Apply

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GPU Utilization %		Global State	
GPU1: 98	GPU2: 96	FPS: 20.46	Scaling (4,4): 3.79
GPU3: 98	GPU4: 98	GFlops: 2765.9	Latency: 173.63



Four GPUs  
Four pipes  
Utilization: 96%+

- FPS: 20.46
- Scaling: 3.79 – Near linear Scaling!
- Note NO gaps in the profiler

# Mobile Crowdsourcing Video Scene Reconstruction

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# Thank You

For more information please contact

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