

LightFields.jl: Fast 3D image reconstruction for VR applications

Héctor Andrade Loarca

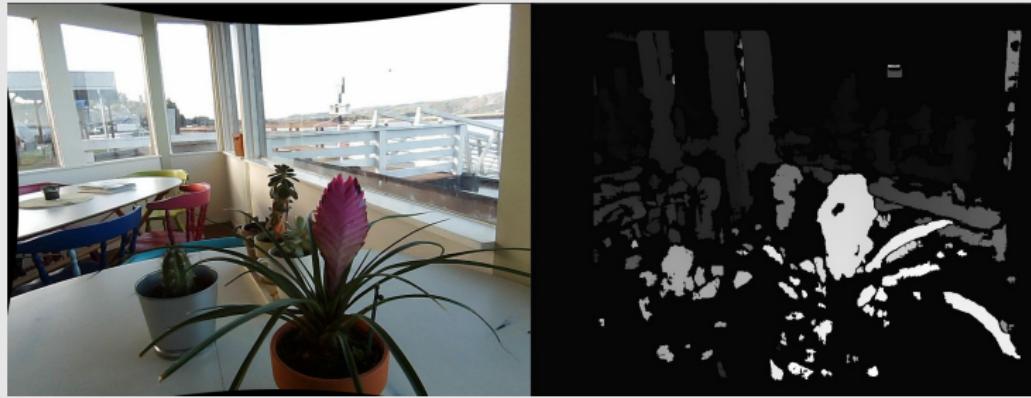
Technical University of Berlin, BMS

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PyData 2018



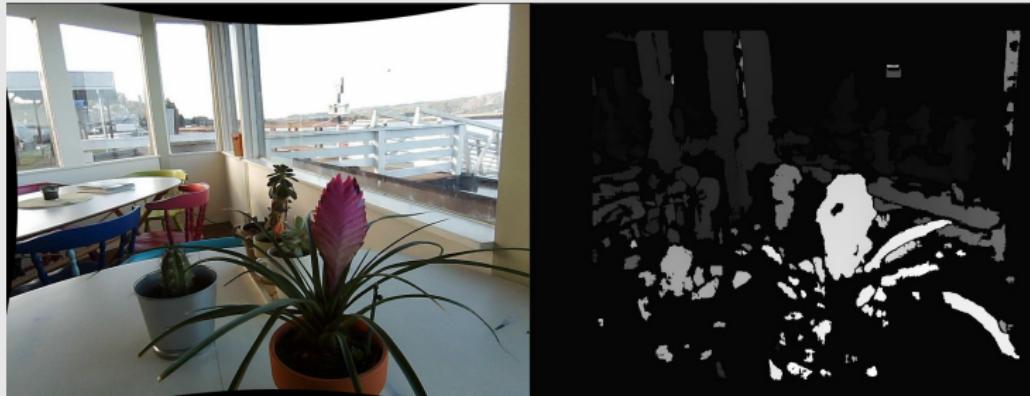
Main goal

- ▶ Present a novel technique to reconstruct the **depth map** of a scene from a limited number of views. This can be applied in view synthesis and rendering for free viewpoint VR.



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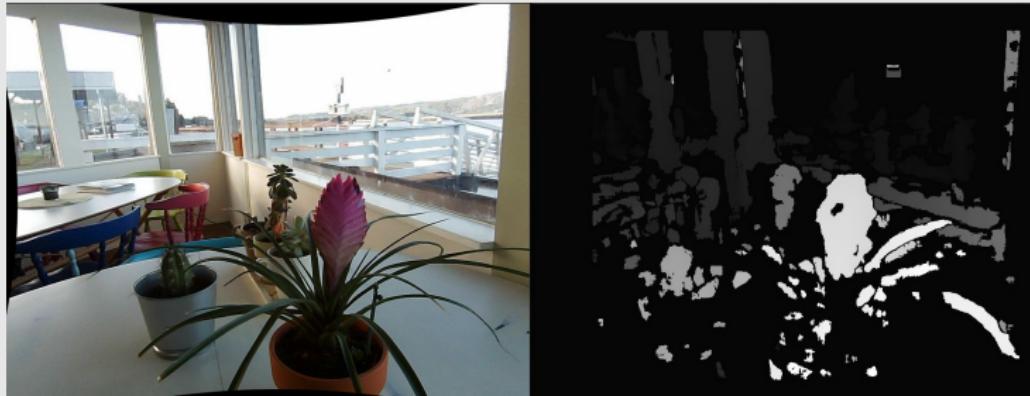
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- ▶ Explain the main building blocks of the technique: Light Field and Shearlets.

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- ▶ Present a novel technique to reconstruct the **depth map** of a scene from a limited number of views. This can be applied in view synthesis and rendering for free viewpoint VR.



- ▶ Explain the main building blocks of the technique: Light Field and Shearlets.
- ▶ Show a free hardware/software implementation using julia, python and Raspberry Pi.

What is a Light Field?

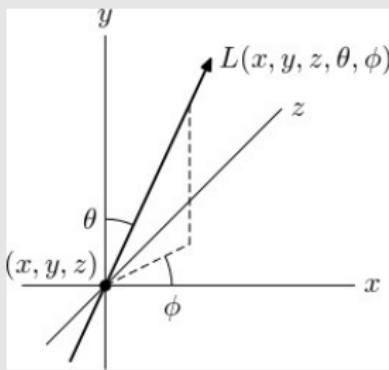
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- ▶ Propagation of light rays in the 3D space is completely described by a 7D continuous function $L : \mathbb{R}^7 \longrightarrow \mathbb{R}^3$, $L(x, y, z, \theta, \phi, \lambda, \tau)$ called the **plenoptic function**

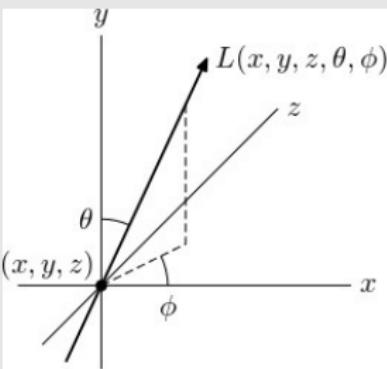
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- ▶ L can be simplified to a 4D function L_4 , called **4D Light Field** or simply **Light Field**, which quantifies the intensity of static and monochromatic light rays propagating in half space.

4D Light Field Representation

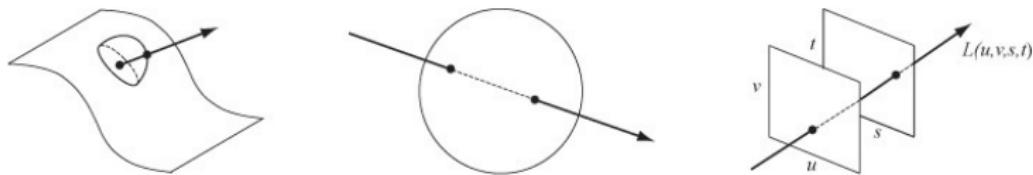


Figure: Three different representation of 4F LF. Left: $L_4(u, v, \phi, \theta)$. Center: $L_4(\phi_1, \theta_1, \phi_2, \theta_2)$. Right: $L_4(u, v, s, t)$.

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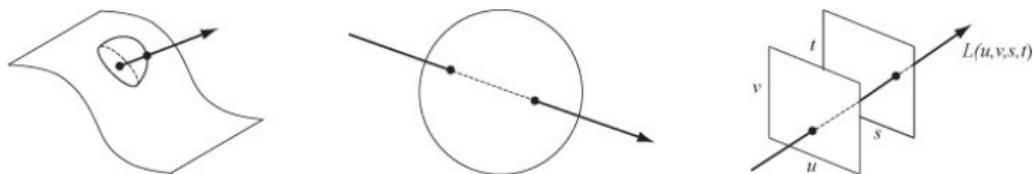


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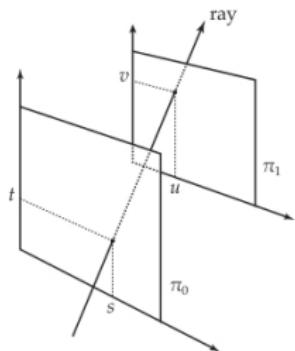


Figure: Used representation: "Two plane parametrization".

From LF to 3D

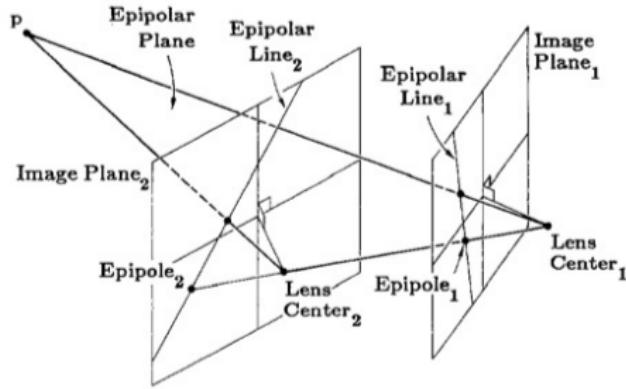
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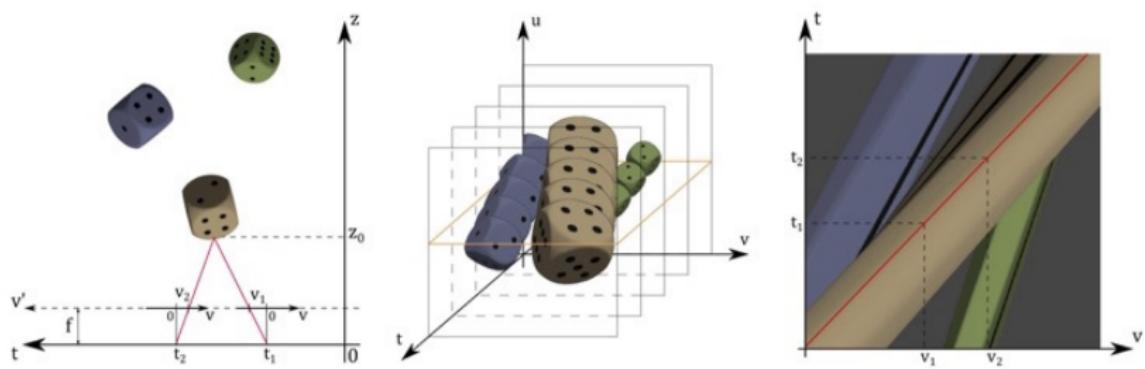
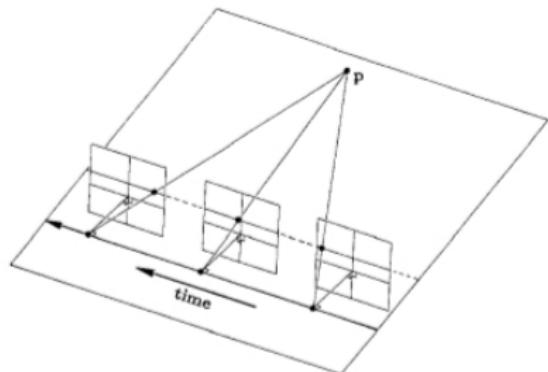
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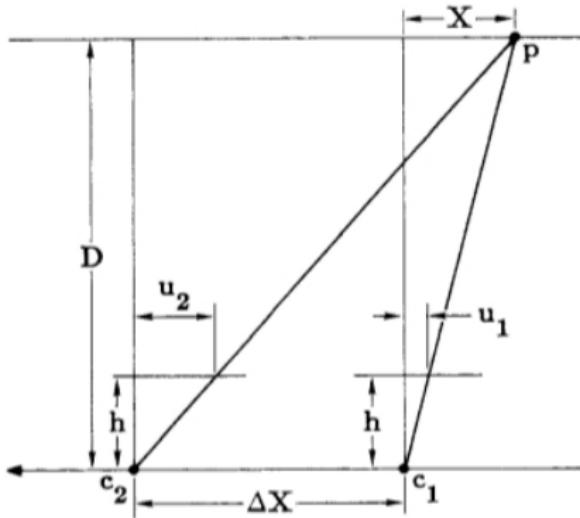
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- ▶ **Epipolar Constraint:** Analysis of object position while assuming the knowledge of the camera motion.



Epipolar Plane Images (EPIs) on Straight Line Trajectories

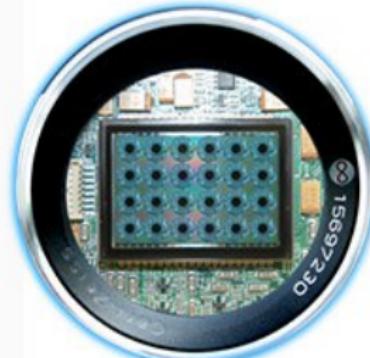


Depth map estimation with EPIs

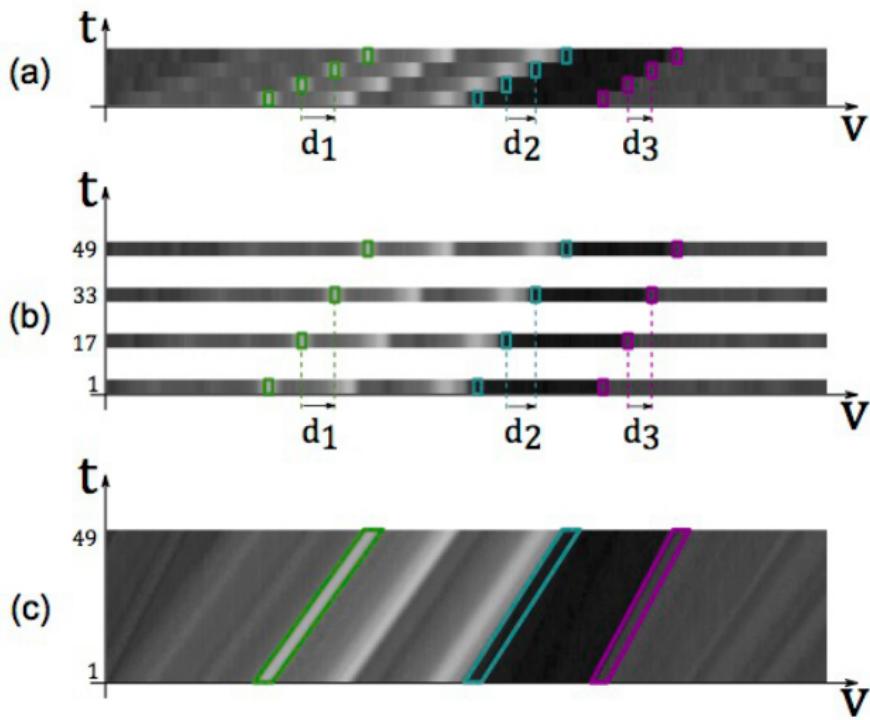


- ▶ **Point-depth formula:** $D = h \frac{\Delta X}{\Delta u} = h \frac{\Delta X}{u_1 - u_2}$.
- ▶ **Sampling rate (Nyquist criterion):** $\Delta X \leq \frac{D_{min}}{h} \Delta u$.

Commercial LF (Epipolar) camera



Our approach: Sub-Nyquist reconstruction via inpainting



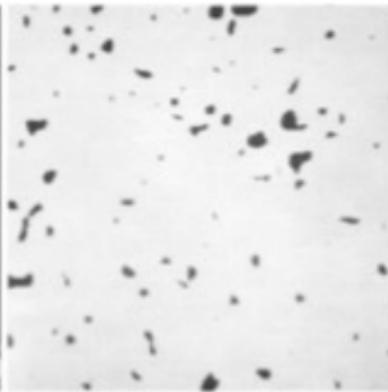
(General) Image inpainting

Mathematical formulation

Recover an image $f \in X$ from known data:

$$g = P_K(f)$$

where P_K is an orthogonal projection onto the known subspace $X_K \triangleleft X$.



How to inpaint?

Frame

A frame for a Hilbert space X is a collection $\Psi = \{\psi_i\}_{i \in \mathcal{I}} \subset X$ satisfying

$$A\|f\|_2 \leq \|\{\langle f, \psi_i \rangle\}_{i \in \mathcal{I}}\|_{\ell^2(\mathcal{I})} \leq B\|f\|_2 \quad \forall f \in X$$

for some $0 < A \leq B < \infty$.

Sparse Regularization/CS approach (Genzel, Kutyniok, 2014):

" If a signal (image) is sparse within a frame Ψ , it can be recovered from highly underdetermined, non-adaptive linear measurements by ℓ^1 -regularization, i.e.

$$\min_{\tilde{f} \in X} \|\{\langle \tilde{f}, \psi_i \rangle\}_{i \in \mathcal{I}}\|_{\ell^1(\mathcal{I})} \quad \text{s.t. } P_K(\tilde{f}) = g = P_K(f) \quad "$$

Frames for images and optimal sparsity

- ▶ Gabor frames (Gabor, 1946).
- ▶ Wavelet frames (Morlet et al., 1984).
- ▶ Curvelet frames (Candès et al., 1999).
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Best N-term approx. error (Donoho, 2001)

Let $\{\psi_\lambda\}_{\lambda \in \Lambda} \subset L^2(\mathbb{R}^2)$ a frame. The optimal best N-Term approximation error for any $f \in \mathcal{E}^2(\mathbb{R}^2)$ is

$$\sigma_N(f, \{\psi_\lambda\}_{\lambda \in \Lambda}) = O(N^{-1})$$

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Error of 2D-wavelets

$$\sigma_N(f, \{\psi_\lambda\}_{\Lambda}) \sim N^{-1/2}$$

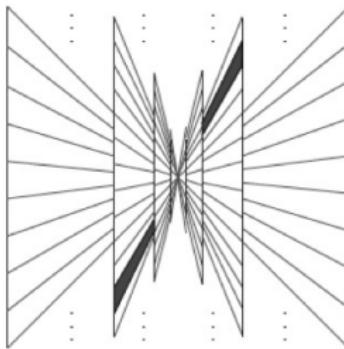
Shearlet Transform (Kutyniok, Guo, Labate, 2005)

Classical Shearlet Transform

$$\langle f, \psi_{j,k,m} \rangle = \int_{\mathbb{R}^2} f(x) \overline{\psi_{j,k,m}(x)} dx$$

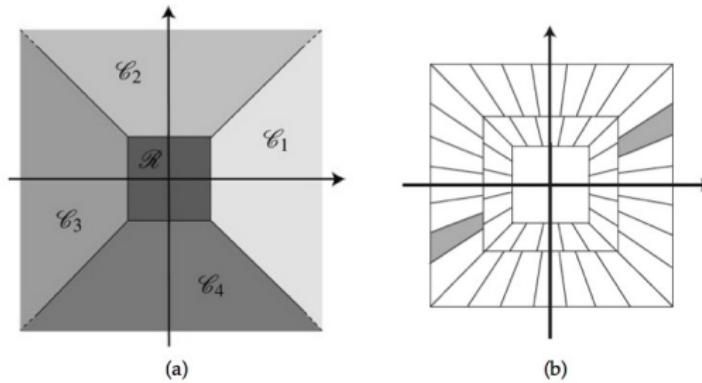
where

$$\mathcal{SH}(\psi) = \{\psi_{j,k,m}(x) = 2^{3j/4} \psi(S_k A_j x - m) : (j, k) \in \mathbb{Z}^2, m \in \mathbb{Z}^2\}$$



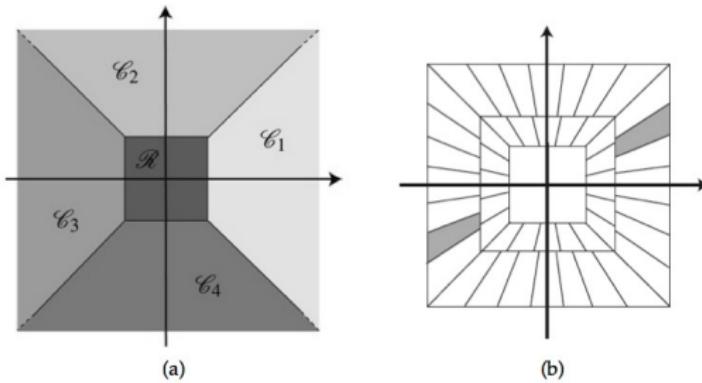
Modification: Cone-adapted Shearlet transform

$$\mathcal{SH}(\phi, \psi, \tilde{\psi}, c) := \mathcal{P}_{\mathcal{R}}\Phi(\phi, c1) \cup \mathcal{P}_{\mathcal{C}_1}\Psi(\psi, c) \cup \mathcal{P}_{\mathcal{C}_2}\tilde{\Psi}(\tilde{\psi}, c)$$



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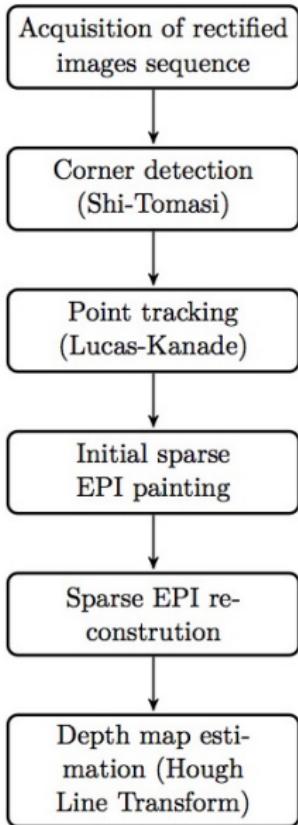


Cone shearlets sparsity (Band limited case: Lim, Labate; 2006),
(Compactly supported case: Kutyniok, Lim, 2011)

Best N -term approximation error

$$\sigma_N(f, \{\psi_{j,k,m}\}_{j,k,m}) \sim N^{-1}(\log(N))^{3/2}$$

Followed Pipeline



Physical Acquisition Setup

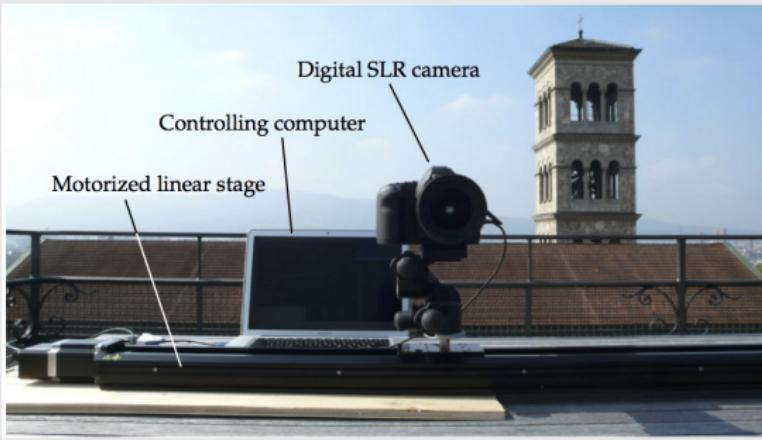
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Point Tracking Results



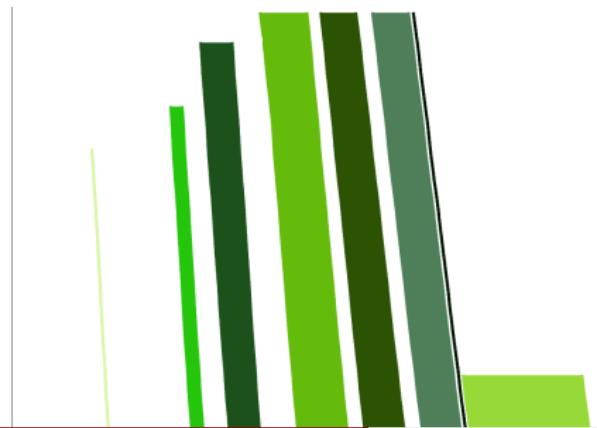
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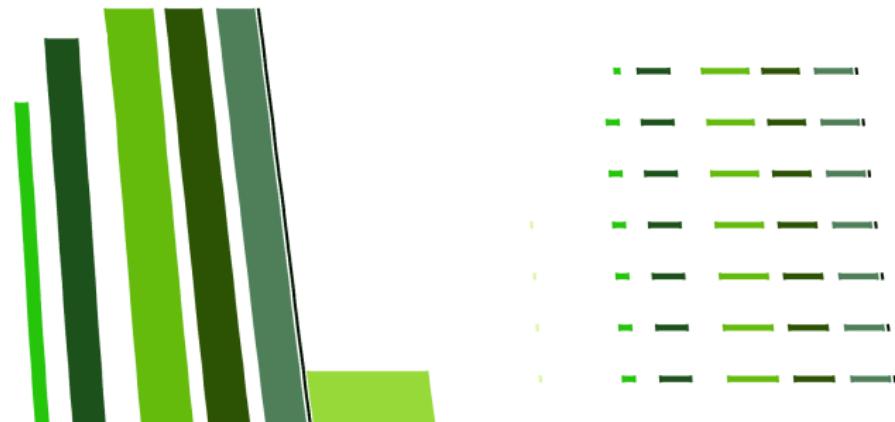
Example of EPI



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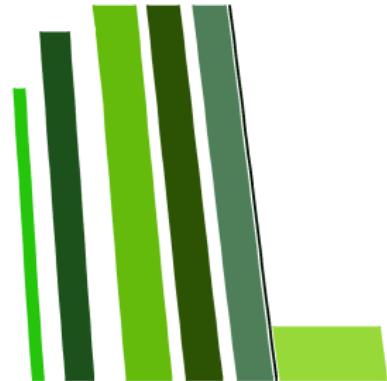
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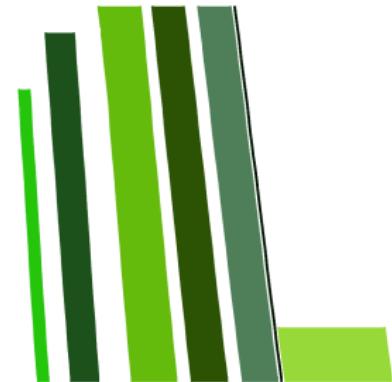
Results on EPIs inpainting



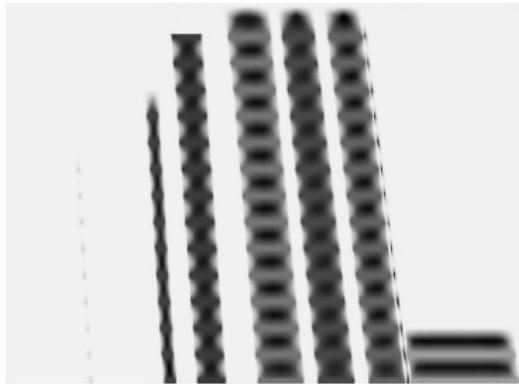
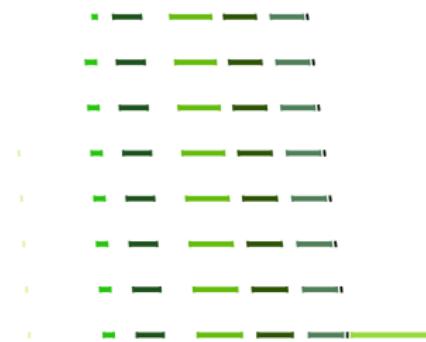
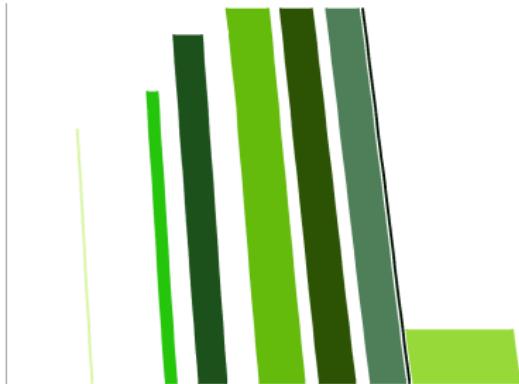
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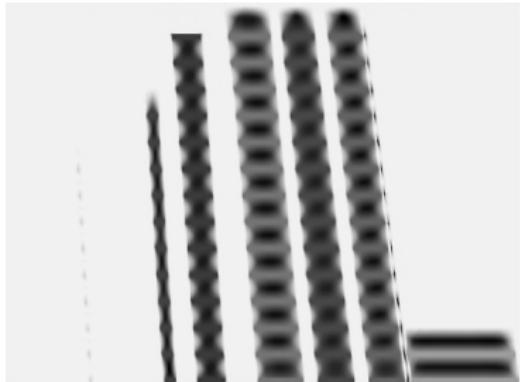
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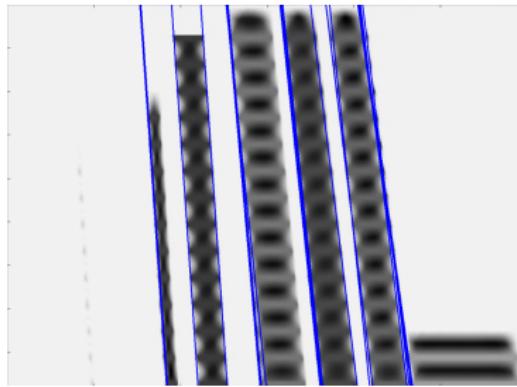
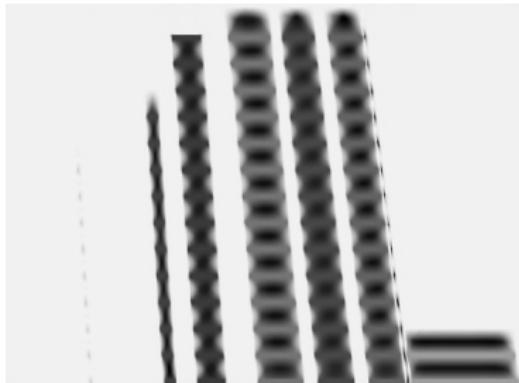
Results on line detection and depth map estimation



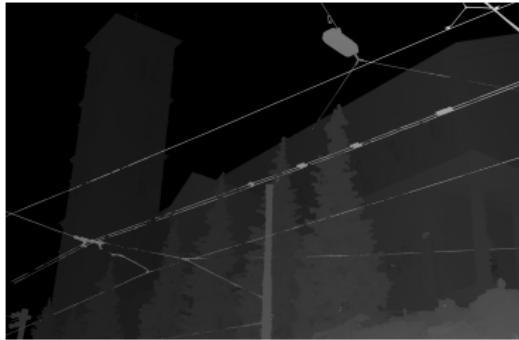
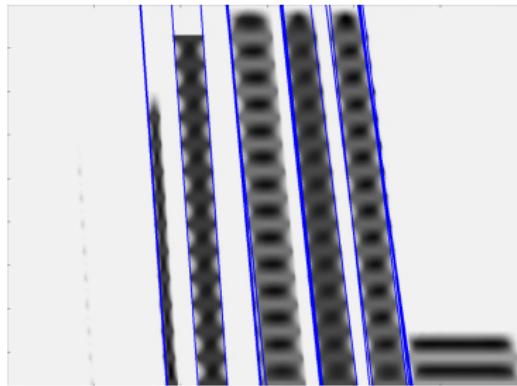
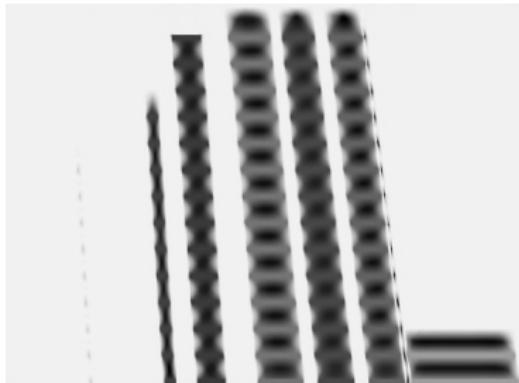
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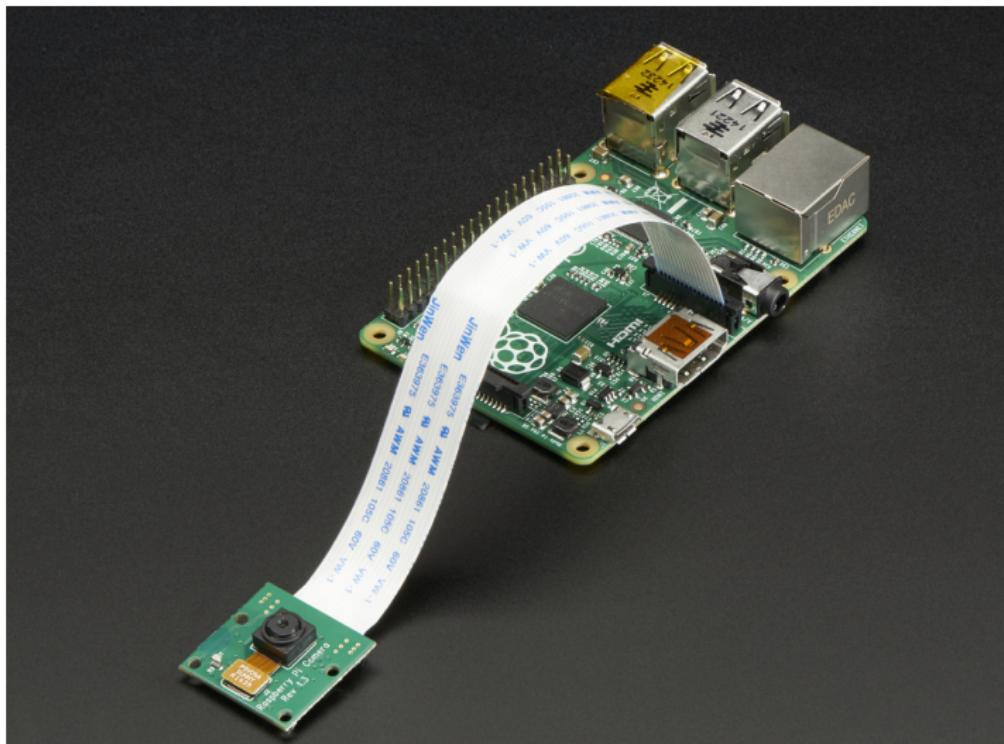


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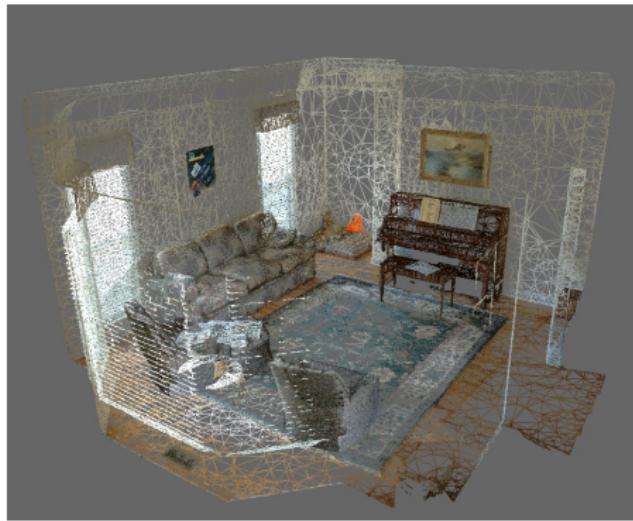


Open Hardware Implementation

Raspberry π + Camera module v2



Future work



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Thanks!

Questions?

