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

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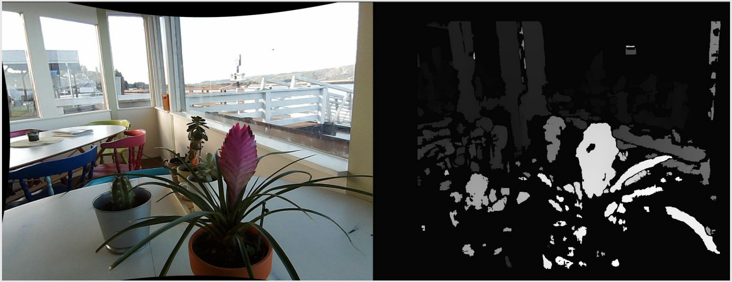
Main goal

- 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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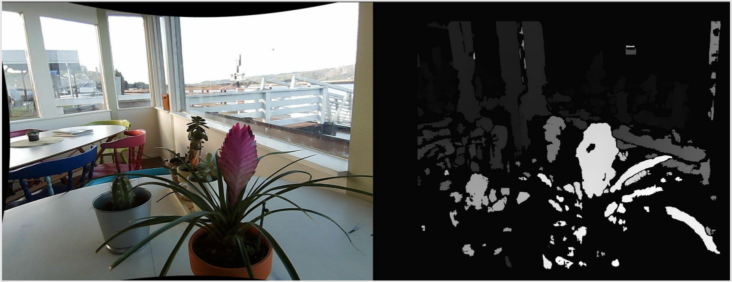

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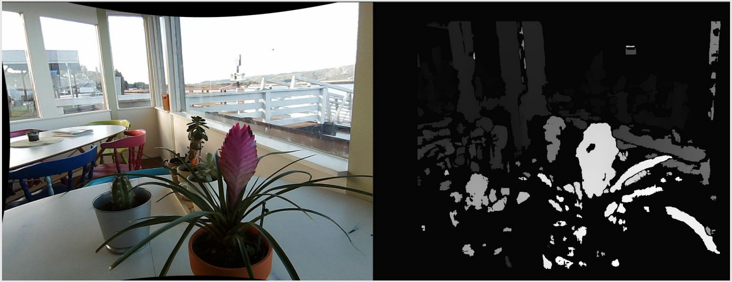

- Explain the main building blocks of the technique: Light Field and Shearlets.
- Show a free hardware/software implementation using julia, python and Raspberry Pi.

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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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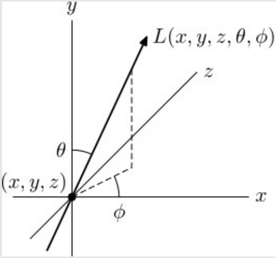

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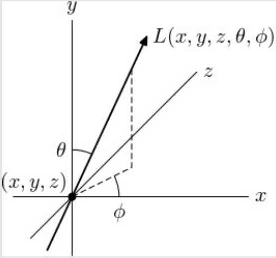

- L can be simplified to a 4D function L_4, called **4D Light Field** or simply **Light Field**, which quantifies the intensity of static and monochromatic light rays propagating in half space.

4D Light Field Representation

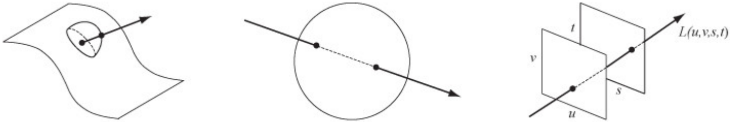

Figure: Three different representation of 4F LF. Left: $L_4(u, v, \phi, \theta)$. Center: $L_4(\phi_1, \theta_1, \phi_2, \theta_2)$. Right: $L_4(u, v, s, t)$.

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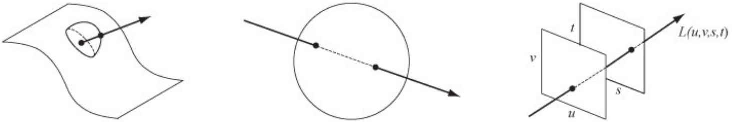

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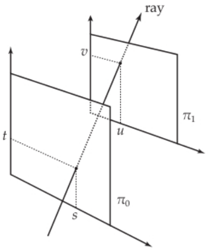

Figure: Used representation: "Two plane parametrization".

From LF to 3D

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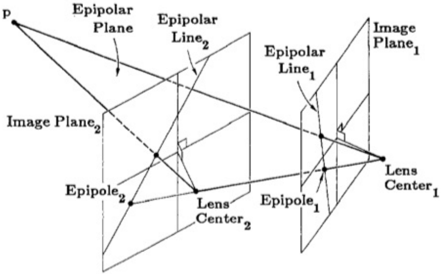
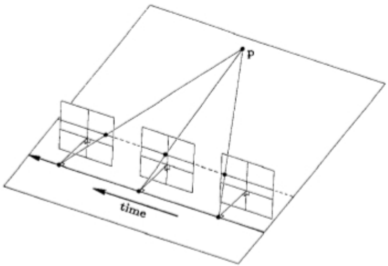
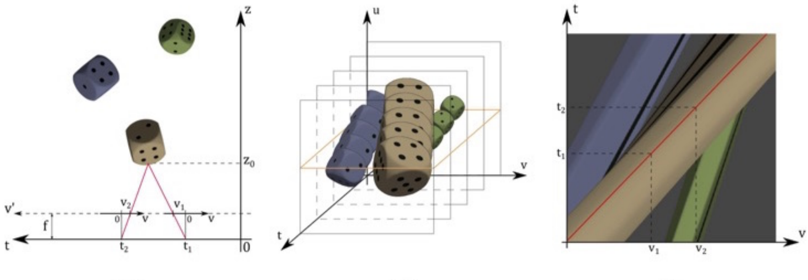
- **Epipolar Geometry:** Generalization of Stereo Vision with more than two views, assuming the epipolar constraint.
- **Epipolar Constraint:** Analysis of object position while assuming the knowledge of the camera motion.

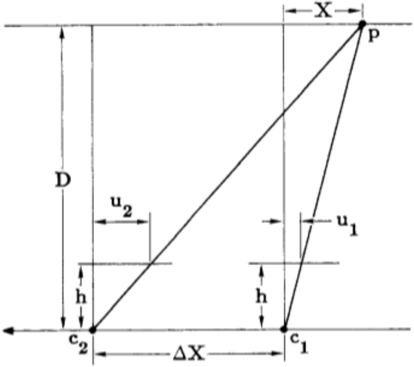


Epipolar Plane Images (EPIs) on Straight Line Trajectories



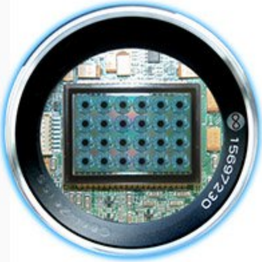


Depth map estimation with EPIs

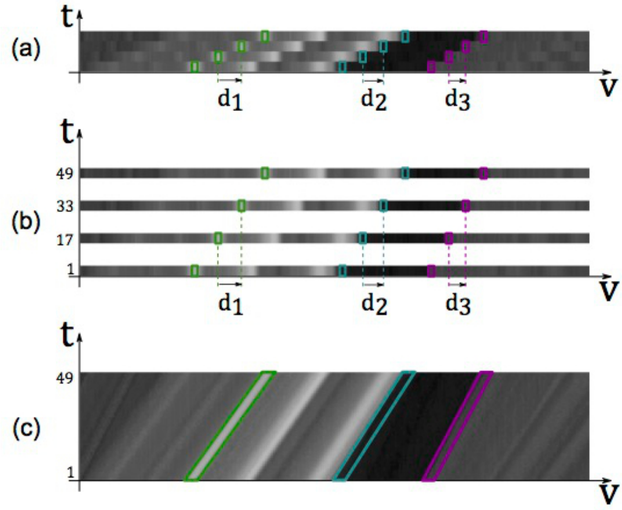


- **Point-depth formula:** $D = h\frac{\Delta X}{\Delta u} = h\frac{\Delta X}{u1-u2}$.
- **Sampling rate (Nyquist criterion):** $\Delta X \leq \frac{D_{min}}{h}\Delta u$.

Commercial LF (Epipolar) camera



Our approach: Sub-Nyquist reconstruction via inpainting



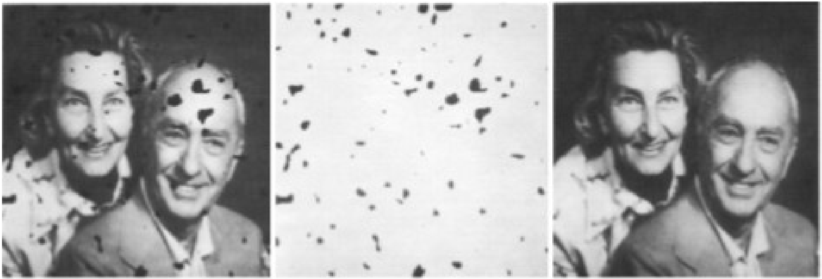
(General) Image inpainting

Mathematical formulation

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

$$g = P_K(f)$$

where P_K is and 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).
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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

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

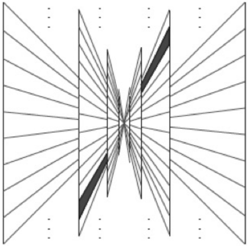
Shearlet Transform (Kutyniok, Guo, Labate, 2005)

Classical Shearlet Transform

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

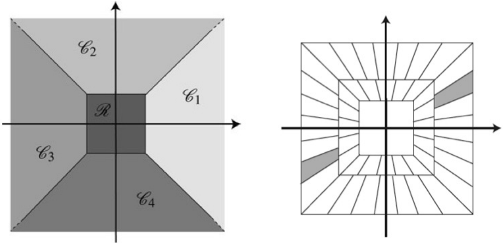
where

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



Modification: Cone-adapted Shearlet transform

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



(a) (b)

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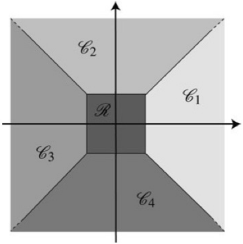

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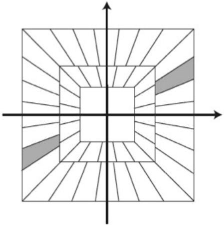


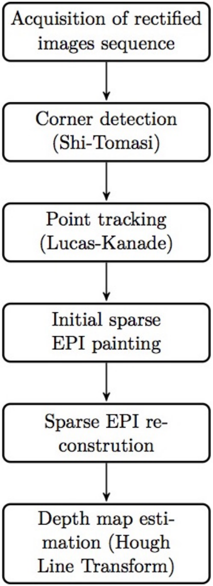
(b)

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



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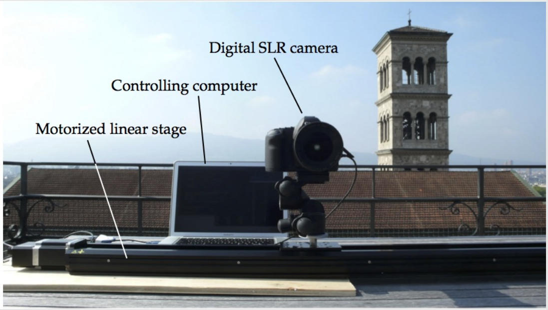

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Point Tracking Results

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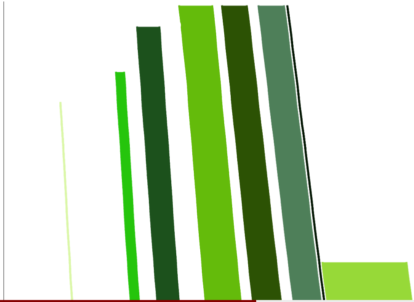

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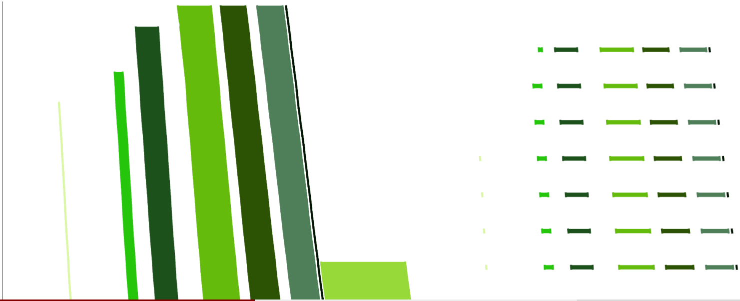

Results on EPIs inpainting

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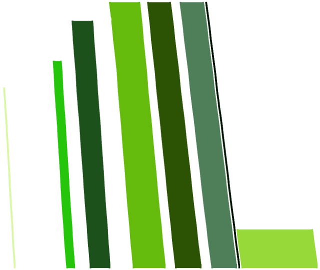

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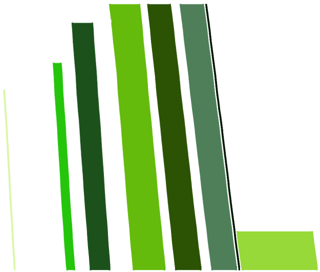

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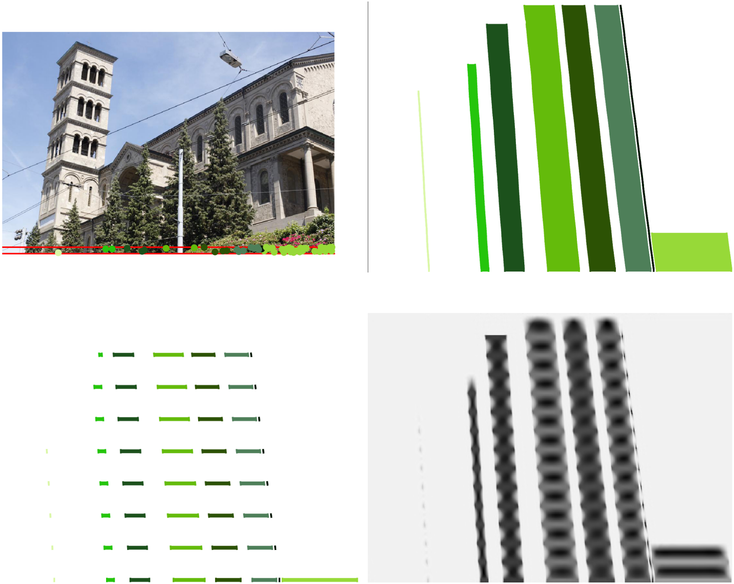

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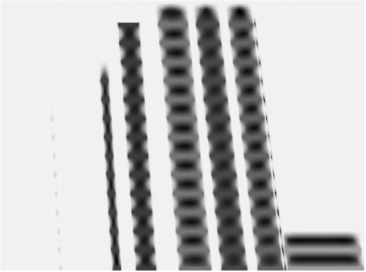

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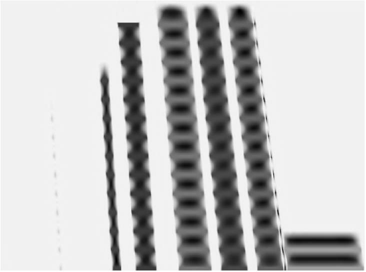

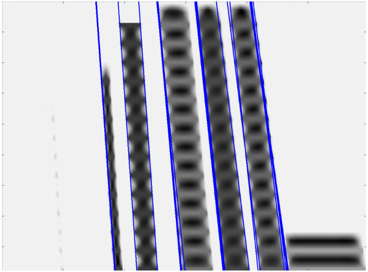

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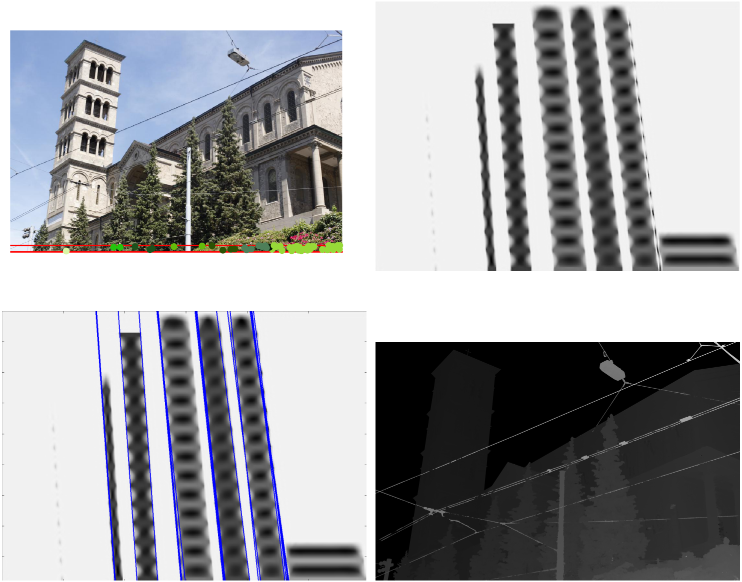
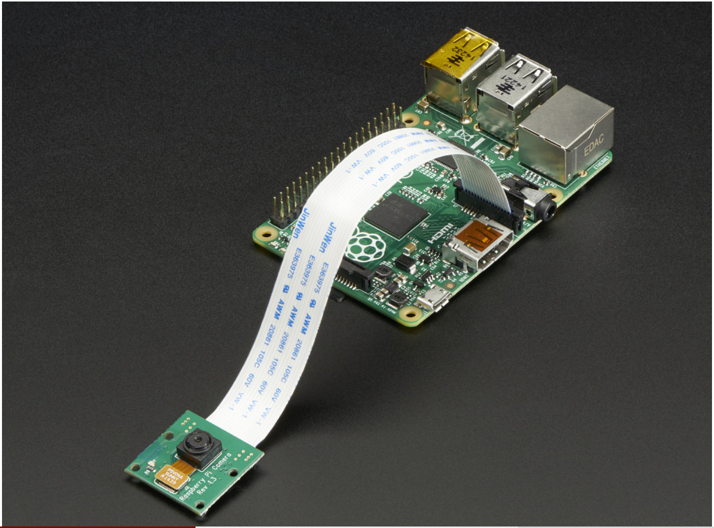
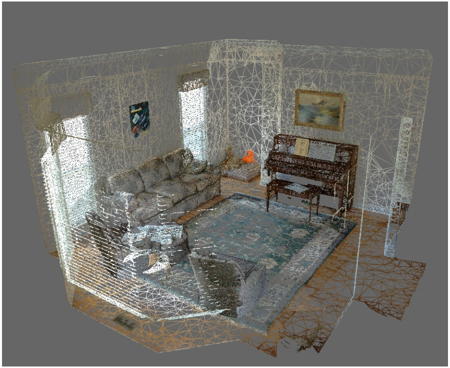


Raspberry π + Camera module v2



Future work



Thanks!

Questions?