All-Photon Imaging through Scattering Media with a Learning Based Prior

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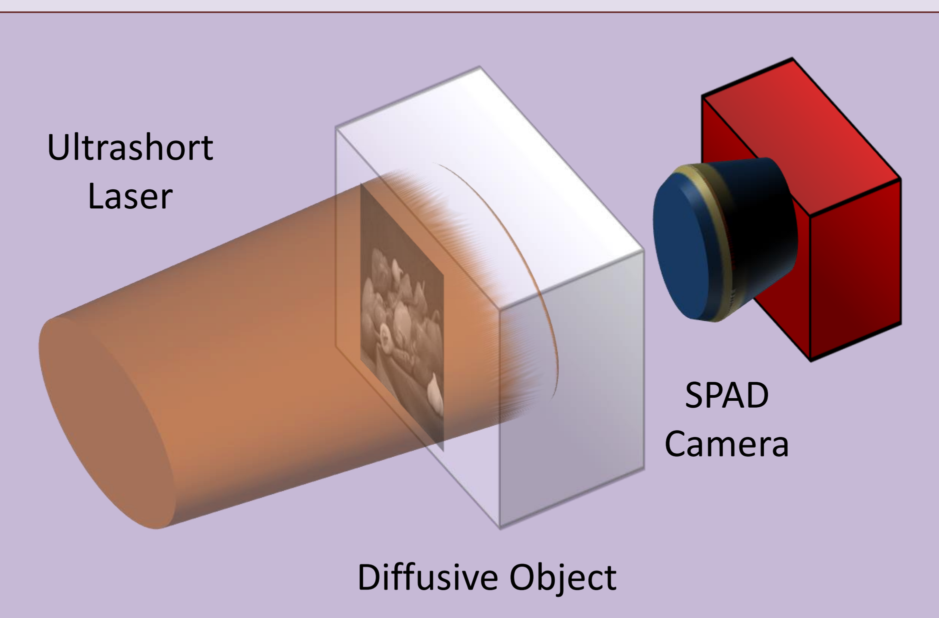
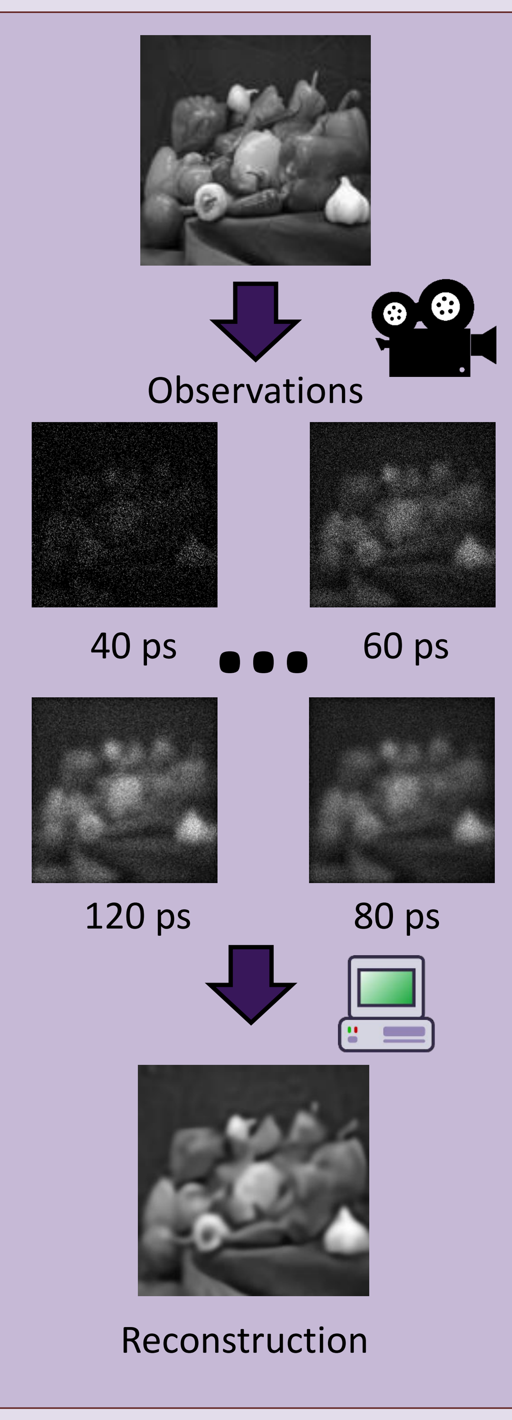
Introduction

Imaging through **scattering media** finds applications in diverse fields from biomedicine to autonomous driving. However, interpreting the resulting images is difficult due to blur caused by the scattering of photons within the medium. Transient information, captured with **fast temporal sensors**, can be used to significantly improve the quality of images acquired in scattering conditions. Photon scattering, within a highly scattering media, is well modeled by the **diffusion approximation** of the **Radiative Transport Equation (RTE).** Its solution is easily derived which can be interpreted as a **Spatio-Temporal Point Spread Function (STPSF)**. In this paper, we first discuss the properties of the ST-PSF and subsequently use this knowledge to **simulate transient imaging** through highly scattering media. We then propose a framework to invert the forward model, which assumes **Poisson noise**, to recover a **noise-free, unblurred image** by solving an optimization problem.





An ultrafast pulsed laser source illuminates a **transmissive object** which is placed directly in front of a highly scattering medium. A **streak camera** is able to resolve the arriving photons in time. Ballistic and scattered photons arrive **at different times** since scattered photons travel a longer path. The spatio-temporal imaging system is modeled with a **time-dependent point spread function** computed from the **RTE**. Inversion of this model allows **reconstruction** of a noise free, **deconvolved** image.

Computing the Point Spread Function

Radiative Transport Equation (RTE):

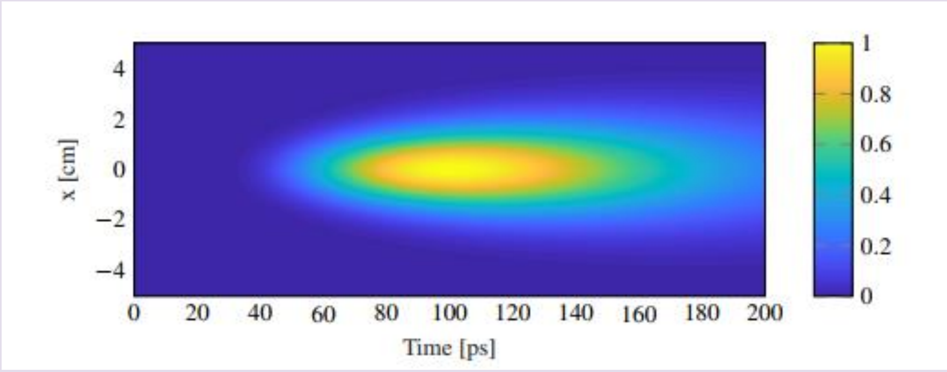
$$\frac{1}{c}\frac{\partial u(r,t)}{\partial t} = D\nabla^2 u - \mu_a u + S$$

$$and \quad u(r,0) = f(r)$$

$$and \quad D = \frac{1}{3(\mu_a + (1-g)\mu_s)}$$

Solution of RTE:

$$h(x,y,y;z_0) = \frac{c}{(4\pi cDt)^{\frac{3}{2}}} e^{\left(-\frac{x^2+y^2+z_0^2}{4Dct} - \mu_a ct\right)}$$



The energy and width of the ST-PSF grow in time. Initial time slices have **little blurring**, but **low energy**. Later time slices have **more energy**, but **significant blurring**. The ST-PSF was created with *ms* = 5cm-1, *ma* = 1cm-1, *g* = 0:99 and a scattering volume with depth 3cm.

Poisson Likelihood

Image formation mode: $I(x,y;t) = \int o(x-x',y-y') \cdot h(x',y',t;z_0)dx'dy'$

Likelihood for image at time k: $P(m^k|o) \propto \prod_{j=1}^{N} (e_j^T H^k o)^{m_j^k} e^{-e_j^T H^k o}$

Poisson Likehood for all images: $P(m^1,\dots,m^k|o) \propto \prod_{k=1}^{K} P(m^k|o)$

Log – Likelihood: $L(o) = \text{const.} + \sum_{k=1}^{K}\sum_{j=1}^{N} e_j^T H^k o - m_j^k \log e_j^T H^k o$

Plug-and-Play Prior Based Deconvolution

Cost – Function with regularizer ϕ: $o = \arg\min_o \mathrm{L(o)} + \beta\phi(o)$

Construct Augmented Laugrangian: L_λ

$$L_\lambda(o,v,u) = L(o) + \beta\phi(v) + \frac{\lambda}{2}||o - v + u||_2^2 - \frac{\lambda}{2}||u||_2^2$$

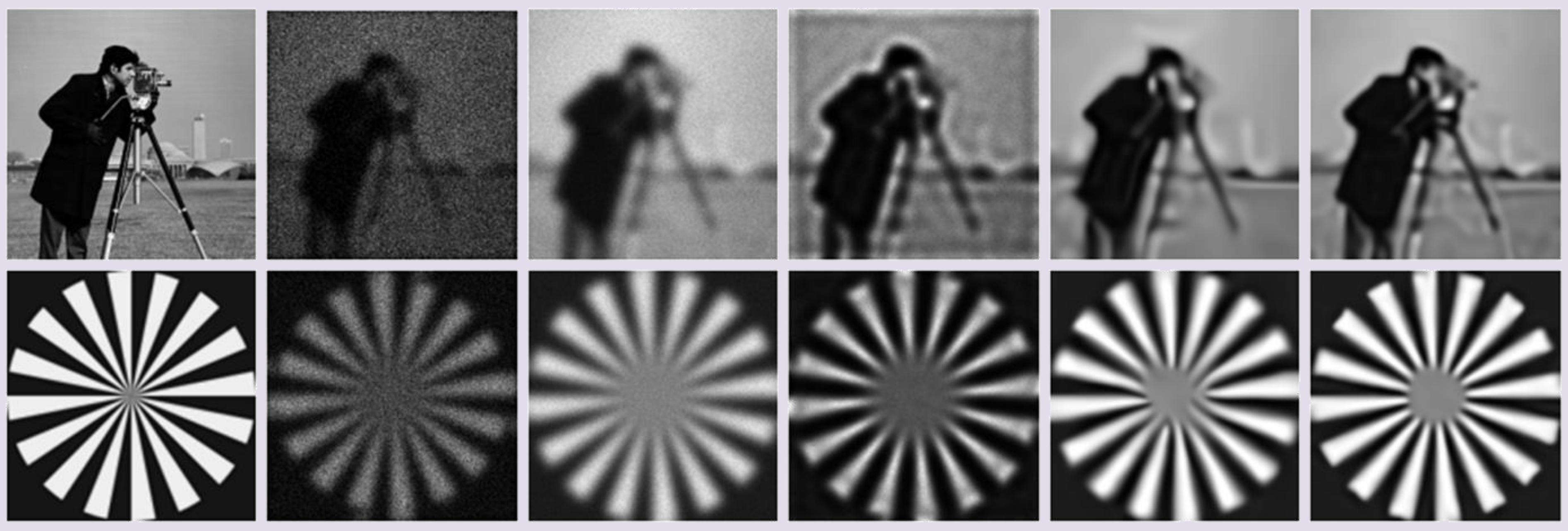
$$o_{i+1} = \arg\min_o \mathrm{L(o)} + \frac{\lambda}{2}||o - v_i + u_i||_2^2 - \frac{\lambda}{2}||u||_2^2$$

$$v_{i+1} = \arg\min_v \mathrm{L(o)} + \frac{\lambda}{2}||o_{i+1} - v + u_i||_2^2 - \beta\phi(v)$$

Replace with Deep Denoiser [5]: $v_{i+1} = \mathbf{FFDNET}_{\boldsymbol{\sigma}}(o_{i+1} + u_i)$

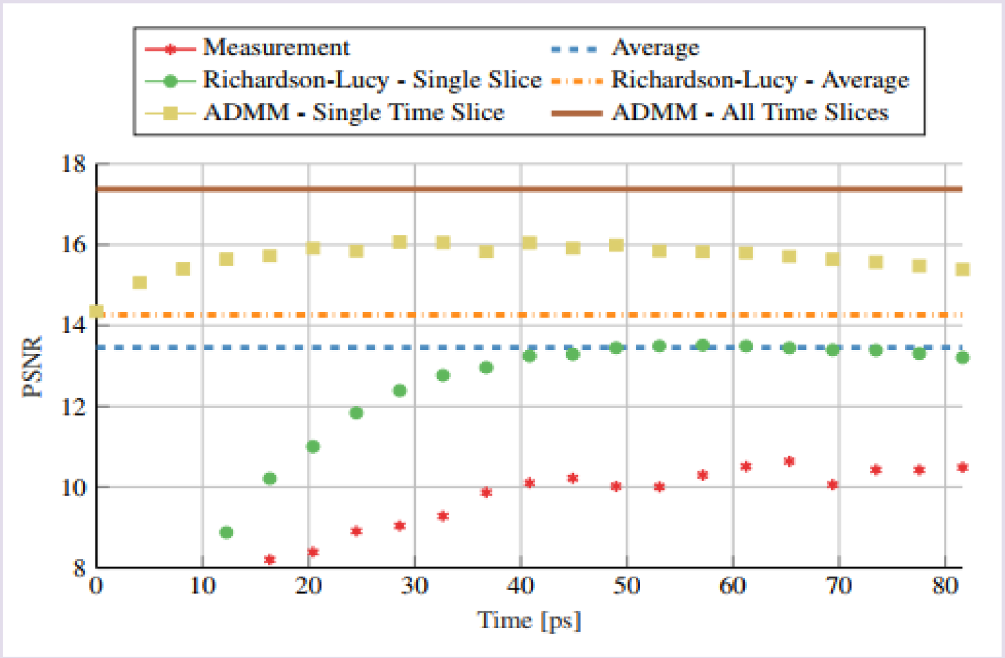
$$u_{i+1} = u_i + (o_{i+1} - v_{i+1})$$

Results



(a) Ground Truth (b) Weakly scattered (c) Time average (d) RL Deconvolution (e) P&PP Single Time (f) P&PP All times

Visual evaluation of the proposed reconstruction algorithm for two **simulated images**. Weakly scattered images are subject to **heavy noise** (b), while later times are **heavily blurred** with better photon statistics (c). Images (d) show deconvolution with Richardson-Lucy. The proposed algorithm was applied for a single image of an early time, see (e), and for a reconstruction considering the full temporal image stack, see Images (f). Reconstruction with the temporally resolved images shows the best reconstruction result.



The figure shows the PSNR for raw measurements, Richardson-Lucy deconvolution and the proposed ADMM framework. Points represent reconstruction of only one time slice, lines mean that photons from all time slices are used

References

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