# Plenoptic Based Super-Resolution For Omnidirectional Image Sequences

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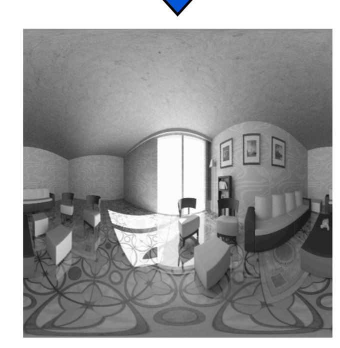
## 1. Introduction

### Problem Description

- From a set of omnidirectional low resolution images, reconstruct an high resolution image
- Images come from a moving camera
- Camera motion is unknown



### Motivations

- Images from omnidirectional imagers suffer from severe distortions -> classical algorithms perform poorly
- Omnidirectional cameras offer poor resolution
- The problem has not been fully addressed [1]

### Main Contributions

⋆Full flexible framework for Super-Resolution

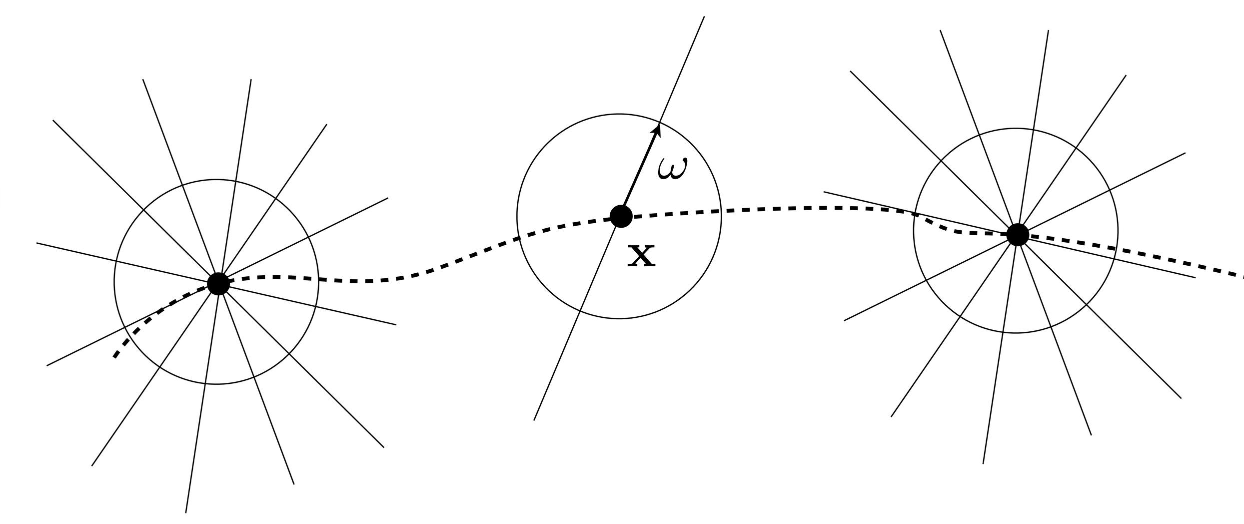
⋆Naturally handle omnidirectional geometry and irregular sampling through a Graph-Based representation of the underlying Plenoptic Function

## 2. Framework Description

### Modelization

Plenoptic function

$\mathcal{L}(\mathbf{x}, \omega)$

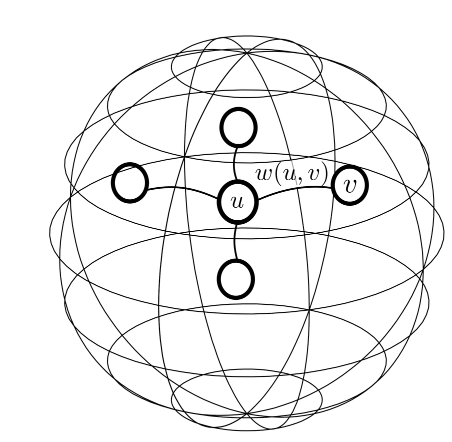



An image can be interpreted as a sample of the plenoptic function

$$l = \mathcal{L}(\mathbf{x}_i, \Omega_o) \qquad \Omega_o = \{\omega_k : k = 1, 2, \cdots, M_l\}$$

### Graph Representation

- We represent an image using a graph
- The connection scheme is defined through geodesic distances on the sphere
- We can define **stable differential operators** on graph [3]




## 3. Problem Formulation

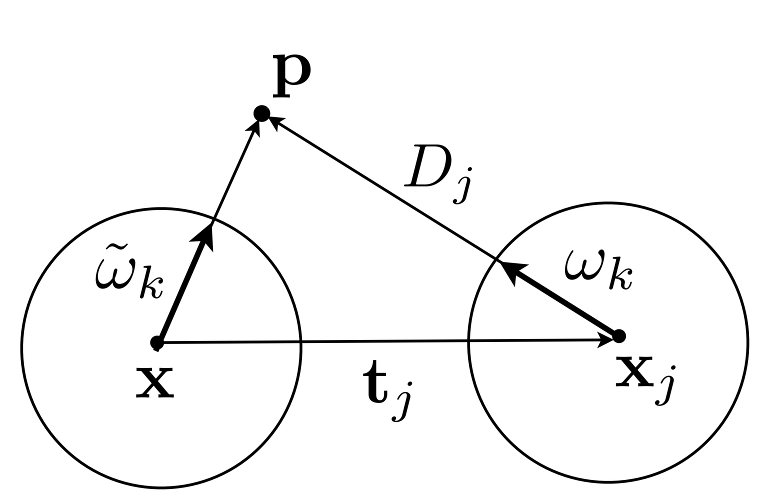
### Plenoptic Registration

$$\mathbf{p} = D_j \omega_k$$

$$\tilde{\omega}_k = \frac{\mathbf{p} - \mathbf{t}_j}{\|\mathbf{p} - \mathbf{t}_j\|}$$

$$\mathcal{L}(\mathbf{x}, \tilde{\omega}_k) = \mathcal{L}(\mathbf{x}_j, \omega_k)$$

$$\Omega_l = \bigcup_j \{\tilde{\omega}_k\}^j$$




Light ray geometry between position $\mathbf{x}$ and $\mathbf{x}_j$

### Depth and Camera Motion Estimation

- Depth and camera motion need to be estimated
- We perform the task as described in [2]

### Variational Formulation

Data on full set of directions

$$f = \mathcal{L}(\mathbf{x}, \Omega)$$

Data from available frames

$$b = \mathcal{L}(\mathbf{x}, \Omega_l)$$

TV inpainting scheme on graphs

$$f^* = \underset{f}{\operatorname{argmin}} \|b - \Phi f\|^2 + \lambda \sum_v \|\nabla_v^w f\|$$

The functional can be solved using convex optimization techniques like the one described in [4]

Differential Operator on Graphs [3]

Local isotropic variation

$$\|\nabla_v^w F\| = \sqrt{\sum_{u \sim v} \left[\left(\nabla^w F\right)(u, v)\right]^2}$$

Gradient

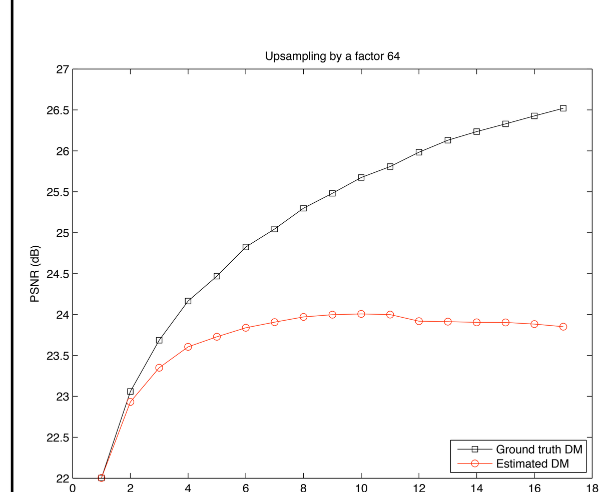
$$(\nabla^w f)(u, v) = \sqrt{\frac{w(u, v)}{d(u)}} f(u) - \sqrt{\frac{w(u, v)}{d(v)}} f(v)$$

## 4. Experimental Results

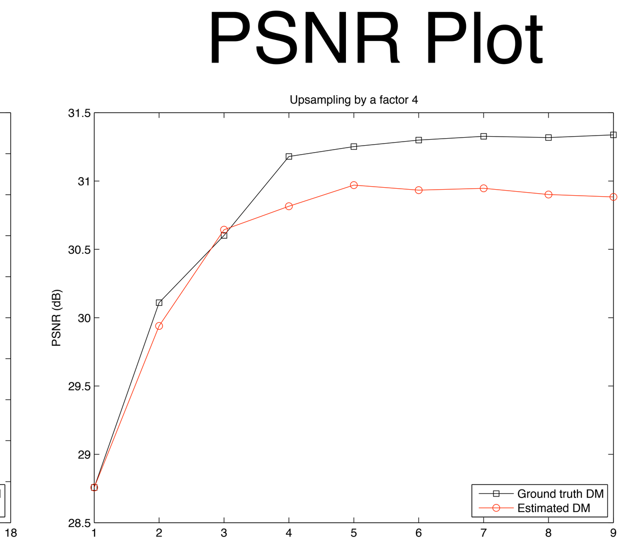
### Experimental Setup

- Syntetic Images generated with Blender
- Original image resolution 512x512
- LR images: 64x64, 128x128, 256x256 - sequences of 17 frames

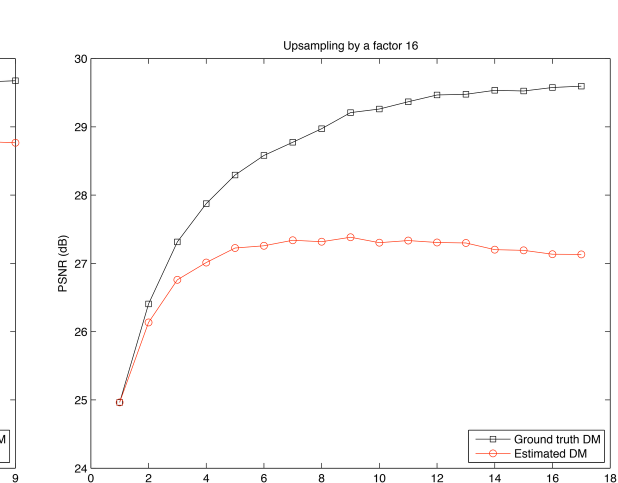
PSNR Plot



256x256 -> 512x512



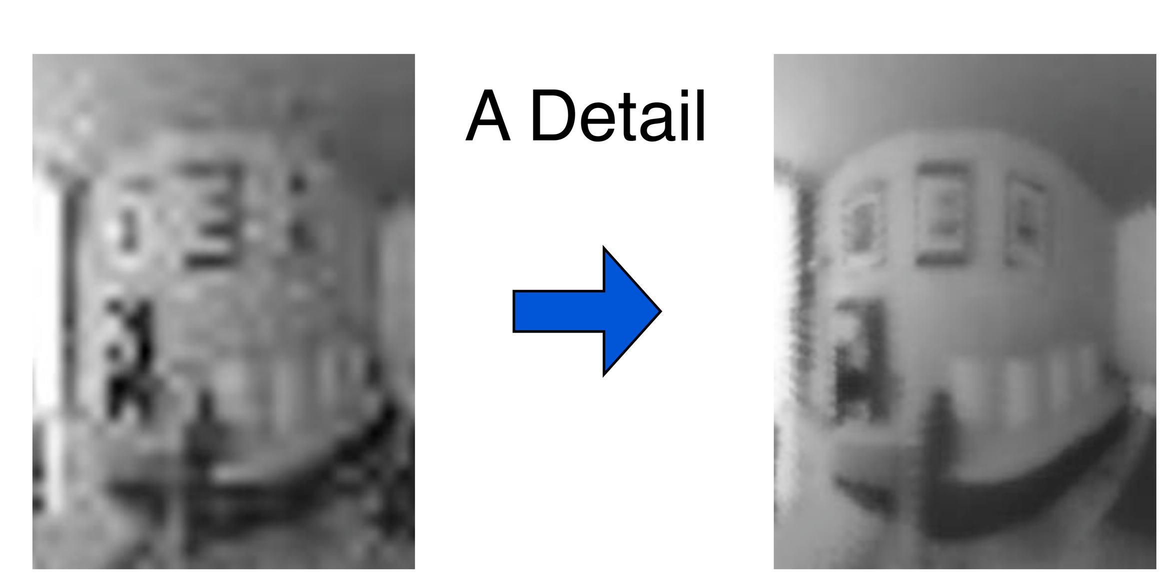
128x128 -> 512x512



64x64 -> 512x512

1 image | 5 images | 9 images | 13 images | 17 images

A Detail



## 5. References

[1] Arican and Frossard. l1 Regularized Super-resolution From Unregistered Omnidirectional Images. Icassp (2009)

[2] Bagnato et al. OPTICAL FLOW AND DEPTH FROM MOTION FOR OMNIDIRECTIONAL IMAGES USING A TV-L1 ... . ICIP (2009)

[3] Zhou and Scholkopf. A regularization framework for learning from graph data. ICML Workshop on Statistical Relational Learning and Its … (2004)

[4] Peyre et al. Non-local Regularization of Inverse Problems. Computer Vision-Eccv 2008 (2008)

Thursday, September 23, 2010