Super-Resolution on Light Field Data

An MPhil project proposal

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Abstract

Light field image data has been used in many applications including post-capture image refocusing or 3D image display. Thanks to the commercialisation of the light field camera, we could foresee the light field data massively available in the near future. However, due to the fundamental trade-off between the spatial and angular resolution, computational approach to increase the resolution of raw data is desired. For this project, I propose to survey the method on the light field super resolution, particularly in angular domain and implement an application with statistical approach.

1 Introduction, approach and outcomes

Light Field and Light Camera

Light field is a 4D vector field that measures the intensity of the light given the spatial coordinates and angular direction. Comparing with traditional 2D images, light field enable us to (1) render images with with post-capture control of focus and depth-of-field [1], (2) render images from different viewpoints [1] within a range without extra depth information or feature matching (3) construct real 3D images without effect of visual contractions. [2]

Thanks to recent commercialisation of light field camera [3], capturing a dense camping of the light field became feasible for real world applications. However, light field camera with modest sensor often face the trade-off between spatial and angular resolution - either sample densely in the spatial domain and sparsely in the angular domain or vice versa. Thus, there is great interest to increas the resolution of the raw captured light field sampling with the computational method.

Super Resolution Techniques

Super resolution refers to a class of techniques that enhance the resolution of an imaging system. For light field system, one would enhance the resolution either in spatial domain or in angular domain.

Spatial super resolution of light field images could be regarded as a special case for constructing high resolution image from multiple low resolution images. And the angular super resolution is equivalent to the synthesis of novel view from new viewpoints.

Comparing with more generalized super-resolution problems, light field data have several advantages for super resolution tasks: 1) the camera position is known 2) the camera positions are regularly distributed on the grid 3) A decent amount of relevant images are available. Thus, many techniques that

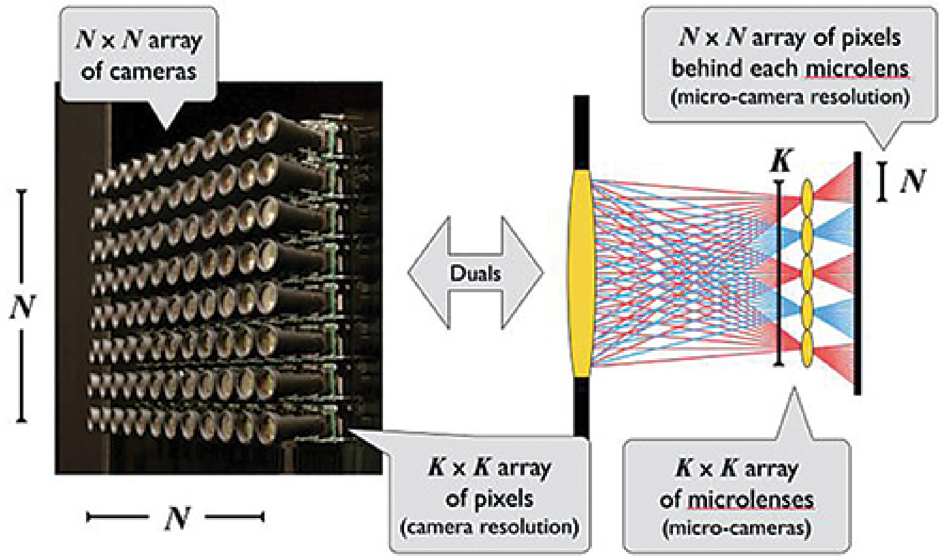

Figure 1: it shows how two different design of light field camera trade-off between spatial and angular resolution, while the camera system on the left has spatial resolution of K^2 and angular resolution of N^2, the camera system on the right has spatial resolution of N^2 and angular resolution for K^2

are specific to the light field data has been proposed. To the best of my knowledge, these techniques could be categorised into three major ways.

1. Statistical method by the restoration techniques [4] [5] [6] : The low resolution sampling was treated as the product of the noise and down-sample operator from the high resolution light field.
2. Learning base methods [7] [8]: some have also successfully tried to use popular deep learning techniques to train an end to end convolutional neural network.
3. Hybrid image system [9]: some tried to use a hight spatial resolution camera in addition to the light field camera to enhance the spatial resolution of the light field data.

Approach

[10] argues that trading off with dense sampling of the spatial resolution and sparse sampling of the angular resolution is essential for camera space in integral photography. Thus, by following this argument, I plan to implement an algorithm to increase the angular resolution given the light field data under the statistical framework view stated as above.

I plan to follow the following pipeline.

- Find depth estimation of spatial slices of light field data
- Register the corresponding points between each spatial slices
- Warp the image slices to the new view

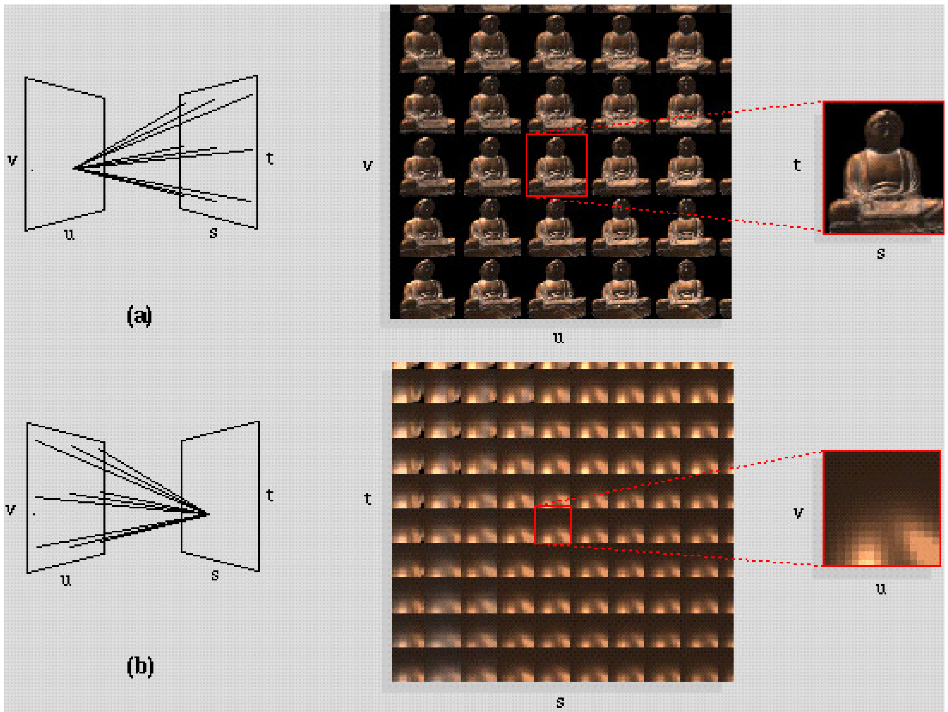

Figure 2: Image from [11]. Light field data could be viewed as a 4D array $L(u, v, s, t)$ where two dimensions (u, v) parametrise the angular variation and (s, t) parametrise the spatial variation. The right top shows the spatial slices if we fix (u, v) and the right bottom shows the angular slices if we fix (s, t)

- Refine from the current result

During this process, many factors including noise, occlusion and non-lambertian surface will present challenges to the quality of our super resolution algorithm. Thus, this project will also investigate if the specific properties of a light field could be utilised to achieve a better result in these challenging settings.

2 Work plan

The work has been divided into 2 weeks chunk for total of 14 chunks. The detailed plan is listed as below. I will count one week as 5 days and weekends would be reserved for emergencies only.

Table 1: **Work Plan**

Week	Milestone	General Description

04/12-17/12 Week 0-1	Prepare the experimental data	• collect light field dataset from the internet (2days) • generate the light field data from 3D model, to obtain ground truth in depth estimation, image registration and interpolated scene for future analysis.(3days) • Devoted to course work (mini-projects). (5 days)
08/12-31/12 Week 2-3	None	• Devoted to course work (mini-projects). (10 days) • Reading relevant techniques used for density estimation, warping frames [12] [13] in spare time.
01/01-14/01 Week 4-5	None	• Devoted to course work (mini-projects). (10 days) • same as above
05/01-28/01 Week 6-7	Implement on the basic naive estimation stage and image registration stage	• Try naive implementation on depth estimation with two view geometry and multiple view geometry. (6 days) • Try naive implementation on image registration with feature matching. (4 days)
09/01-11/02 Week 8-9	Implement the wrap stage and first naive implement of the whole pipeline	• Implement the naive warping algorithm given the image registration result. (3 days) • Implement the naive warping algorithm given the depth estimation result (3 days) • Connect the whole pipeline and evaluate the result. (4 days)
02/02-25/02 Week 10-11	Improve the naive solution with better depth estimation	• Choose to follow a better algorithm for depth estimation related to light field. [14] (10 days)
06/02-11/03 Week 12-13	Improve the naive solution with better registration techniques	• Choose a registration techniques specific to light field. [4]

02/03-25/03 Week 14-15	Improve the naive solution with better wrap scheme	• Implement a better warping algorithm by treating the problem as the image restoration task (MAP frame and energy minimisation). [6] (10 days)
06/03-08/04 Week 16-17	Improve the application with refinement post process	• Investigate techniques for post-process improvement. (10 days)
09/04-22/04 Week 18-19	Finish the first draft on chapters of introduction / background / related work	• write th introduction (2 days) • write the background information (3 days) • summarise the related work (4 days) • collect experiment result from datasets (1 day)
03/04-06/05 Week 20-21	Finish the first draft on chapters of methodology	• prepare additional experiment result from datasets (2 days) • write methodology sections (3 days) • write experiment sections (5 days)
07/05-20/05 Week 22-23	Finish the first draft of the dissertation.	• write the conclusion and result the first draft. (3 days) • extension on a more efficient algorithm (7 days)
01/05-03/06 Week 24-25	Finalise the dissertation.	• Finalise the dissertation (10 days)
04/06-10/06 Week 26	None	Reserved for emergencies.

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