Project proposal: light field image reconstruction

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Introduction

While conventional cameras capture the 2D information of a scene, light field imaging technique provides us with 4D light field distributions, including both spatial and angular information of the scene. With recent development in commercialized light field cameras using microlens arrays, this technique has been on the focus of research for different applications, for example, depth estimation, occlusion removal and scene refocusing. However, one drawback of using a light field camera is its intrinsic tradeoff between spatial and angular resolution. Using microlens arrays to gain angular information lowers the spatial resolution compared to conventional cameras. In this project, we want to address this problem by combining all the 4D light field information to generate super-resolution refocused images of the scene by using computational algorithms and optimization techniques.

Related Work

People have tried different image processing techniques and computer algorithms to reconstruct super-resolved images from light field cameras. Kaushik Mitra et al. proposed a Gaussian mixture model in which a prior based on light field disparity pattern is used and super-resolved images are reconstructed using the LMMSE algorithm [1]. Reuben A. Farrugia et al. looks at the 3D stacks of sub-aperture images (patch volumes) and uses principal component analysis (PCA) and multivariate ridge regression (RR) techniques to reconstruct high resolution images [2]. People also explored deep learning methods using convolution neural networks to tackle this problem. Youngjin Yoon et al. uses a spatial resolving CNN and an angular resolving CNN sequentially to process the light field data [3].

Approach

We are considering to try different priors to recover high spatial and angular resolution images.

1) Compressed sensing. It has been applied to various fields to solve ill-conditioned problems by assuming the data is sparse in some domains [4]. For this application, images at different angles can be highly correlated and compressed sensing may be able to utilize this correlation.
2) Low rank regularization. Recovering high resolution image can be treated as a matrix completion problem. Many low rank models have been proposed to solve this problem, in which some low rank matrices are constructed and a rank constraint is included in the optimization problem [5, 6]. Similar idea can be applied to this problem. A rank constraint is usually relaxed as a nuclear norm constraint to make the problem convex [7].

Many methods have been developed to solve these kind of optimization problems, e.g, POCS, ISTA, FISTA and ADMM. We will choose one based on the problem size and convergence speed.

Milestone & Timeline

2.14 - 2.21	Literature review: What methods and priors have been used for this problem? What else priors can we use to solve this problem? Are there any available public datasets we can use?
2.22 – 3.6	(possible) data collection Determine the model used for the problem Implementation of algorithms Comparison of different priors/algorithms
3.7 – 3.12	Analyze and summarize the results
3.13	Poster presentation

Reference

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