

1 Literature Review

1.1 Structured Light Coding

Some relevant reviews are [1],[2] and slides. A *structured light stereometric system* is similar to a passive stereo system where one of the camera is replaced by a projector. A light source projects light a vertical plane of light that creates a narrow stripe on the scene. The intersection of an illumination plane of known spatial position and a line of sight determines a point. For dense reconstruction of the scene, many images must be taken. To speed up the scanning process, spatially modulated light projector has been suggested, in which multiple illumination planes or rays can be projected simultaneously as part of a single illumination pattern. Spatial-temporal modulation of illumination, i.e. sequentially projecting several patterns, can be used for reliable identification of light planes. To enable acquisition of dynamic scenes, the number of projected patterns used should be as small as possible. Some subtleties

1. It is only necessary to encode a single axis, since a 3D point can be obtained by intersecting a line (pixel of camera image) with a light plane (a single code)
2. Encoding means locating points x in the camera image whose corresponding point y in the projector pattern is a priori known.
3. Intuitively, the projected pattern impose illusion of texture on the object, increasing the number of correspondences, which enables reconstruction.

Horn & Kiryati This paper generalizes Gray code to n-ary code in order to reduce the number of patterns that needs to be projected, (L^K instead of 2^K code words) [3]. The authors draw inspirations from communication theory, where the projector projects unique temporal codes, received at each image plane through a noisy channel and subsequently decoded. Let there be K patterns and L code words (distinct planes of light), we want to encode the indices of vertical light planes $x \in [L]$ using some encoding scheme $f : [L] \rightarrow \mathbb{R}^K$ such that the nearest neighbor decoding $\hat{x}(y) = \arg \min_{x \in [L]} (f(x) - y)$ of a normalized noisy observation $y \in \mathbb{R}^K$ minimizes the probability of depth estimation error. Given the forwarding model,

$$y = f(x) + n \quad \text{where} \quad x \sim \text{Cat}(1/L) \quad n \sim p_n$$

implying $y|x = x \sim p_n(y - f(x))$. We want to minimize the probability of depth estimation error, which roughly proportional to difference between true index x of the plane of light and the estimated index \hat{x} ,

$$\text{minimize}_f \left[\mathbb{E}_{x,y} [(x - \hat{x}(y))^2] = \sum_{x=1}^L p_x(x) \int p_{y|x}(y|x) (x - \hat{x}(y))^2 dy \propto \sum_{x=1}^L \int (x - \hat{x}(y))^2 p_n(y - f(x)) dy \right]$$

This optimization problem is hard. The paper suggest the use of space filling curves as the encoding function and established that Gray code is a special limiting case of the space filling curve. Note here we assume there is no *mutual illumination*, i.e. there is no interval reflection and so the projected codes $f(x)$ is proportional to observation y .

1.2 Image Priors

The choice of regularization has been an important research topic in image processing. Handcrafted priors have been successful in a number of different image recovery tasks. For example, we can choose to enforce task-specific priors: (1) the sparsity of \mathbf{x} with ℓ_1 norm in image deblurring [4] (2) total variation in image denoising [5] (3) cross-channel correlation in color image demosaicing [6] (4) dark channel prior in image

dehazing [7], etc. More exhotically, randomly initialized neural network can inject inductive bias to the optimization and act as image priors. [8]

In addition to hand-crafted priors, there has been interest in algorithm induced priors. Alternating direction method of multipliers (ADMM) is a common convex optimization method for inverse problem where the objective function is separable with respect to the *data term* and the *regularizer*. Each primal update involves an evaluation of a proximal operator, which can be interpreted as performing denoising on some iterate. [9, 10, 11] proposed plug-and-play priors where the choice of regularization is implicitly specified by the denoiser used. [12] proposed an explicit laplacian-based expression for the regularizer and generalizes the method to a number of different iterative optimization algorithms.

The convergence of plug-and-play ADMM is studied by a number of papers. [13] showed fixed point convergence of plug-and-play ADMM. [12] showed convergence of the algorithm under some mild conditions of the denoiser, which are satisfied by some state of the art denoisers like *Block-matching and 3D filtering (BM3D)* [14] and *Trainable Nonlienar Reaction Diffusion (TNRD)* [15]. Most recently, [16] established convergence given that the denoising network satisfy certain Lipschitz condition.

Some proposed to learn proximal operator from data. [17] used a CNN denoiser [18]. Instead of substituting the proximal operator with a denoiser, [19] learns a projection mapping to the space of natural images by training a single neural network and showed impressive results on a number of different linear inverse problems.