



Semidefinite Programming Heuristics for Surface Reconstruction Ambiguities

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Introduction

Several depth cues are locally ambiguous, e.g.

- Shape from shading [1]
- Shape from texture [2]
- Two-light photometric stereo
- Shape from defocus

We consider the problem of reconstructing a smooth surface under constraints that have discrete ambiguities.

Following [1], we convert these problems to a discrete optimization problem. The problem is addressed using semidefinite programming (SDP) relaxation. We improve the rounding phase using a combination of heuristics.

Formulation for two-fold ambiguities

Linear surface representation: $z(x, y) = \sum b_i(x, y) v_i$

General form: $\operatorname{argmin}_{v,d} \|Av - Bd\|^2, v \in \mathbb{R}^m, d \in \{-1,1\}^n$

Adding smoothness term $\|Ev\|^2$: $\operatorname{argmin}_{v,d} \left\| \begin{bmatrix} E \\ A \end{bmatrix} v - \begin{bmatrix} 0 \\ B \end{bmatrix} d \right\|^2$

Eliminating continuous variables: $v = A^+Bd$

Discrete optimization problem: $\operatorname{argmin}_d \|(AA^+B - B)d\|^2$

$\operatorname{argmin}_X C \cdot X = \sum C_{ij} X_{ij}$

$C = (AA^+B - B)^t(AA^+B - B), X = dd^t$

- Must solve a theoretically hard discrete optimization problem
- Global approach – local decisions affect the entire surface

Standard SDP approach

SDP relaxation: $\operatorname{argmin}_X C \cdot X \text{ s.t. } X_{ii} = 1, X \succeq 0$

Cholesky factorization: $X = RR^t$

Embedding on the unit sphere: $u_i = i\text{-th row of } R, u_i \in \mathbb{R}^n, \|u_i\| = 1$

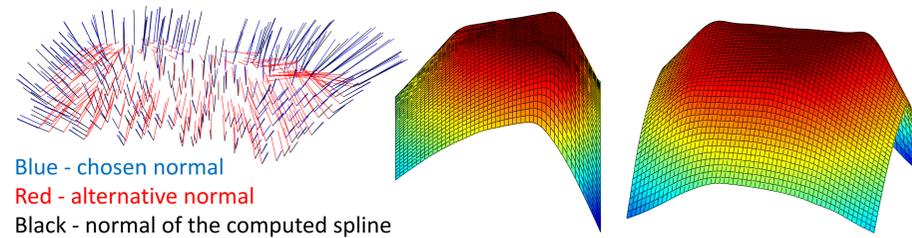
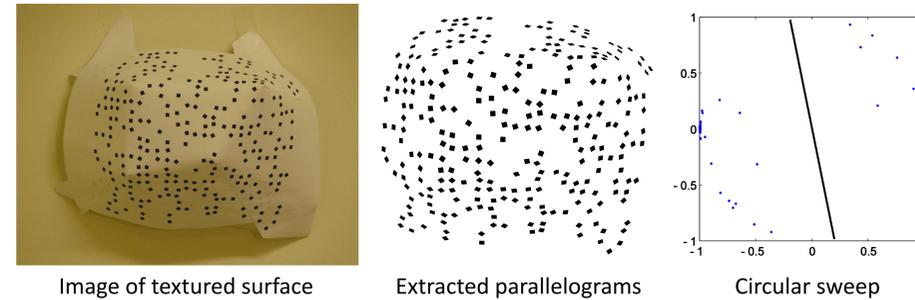
Goemans-Williamson rounding: $d_i = \operatorname{sign}(u_i \cdot N), N$ is a random vector

Our SDP rounding heuristics

- Project the points embedded on the unit sphere onto planes in the subspace of their principle components
- Perform efficient circular sweeps [3]. Each sweep is $O(n^2)$
- Use Kernighan-Lin (K-L) local search for refinement

Example #1: Two-fold ambiguous normals

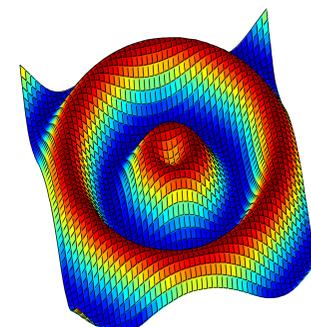
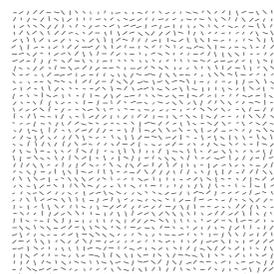
Texture cues provide two choices for the surface derivatives $p = \frac{dz}{dx}, q = \frac{dz}{dy}$
 $(0, \dots, 0, p_i, 0, \dots, 0)d = a_{p_i}v, (0, \dots, 0, q_i, 0, \dots, 0)d = a_{q_i}v$



Example #2: Segments of known length

A segment of 3D length l and image length r_{ij} poses the constraint

$$z_i - z_j = (a_i - a_j)v = \left(0, \dots, 0, \sqrt{l^2 - r_{ij}^2}, 0, \dots, 0\right)d$$



Example #3: Four-fold ambiguous normals

$p = d_1p_1 + d_2p_2, q = d_1q_1 + d_2q_2$
 $d_1, d_2 \in \{-1,0,1\}, d_1 \cdot d_2 = 0$

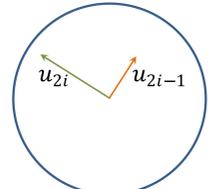
SDP relaxation

$\operatorname{argmin}_X C \cdot X \text{ s.t.}$

$X \succeq 0$

$X_{2i-1,2i-1} + X_{2i,2i} = 1$

$X_{2i-1,2i} = 0$



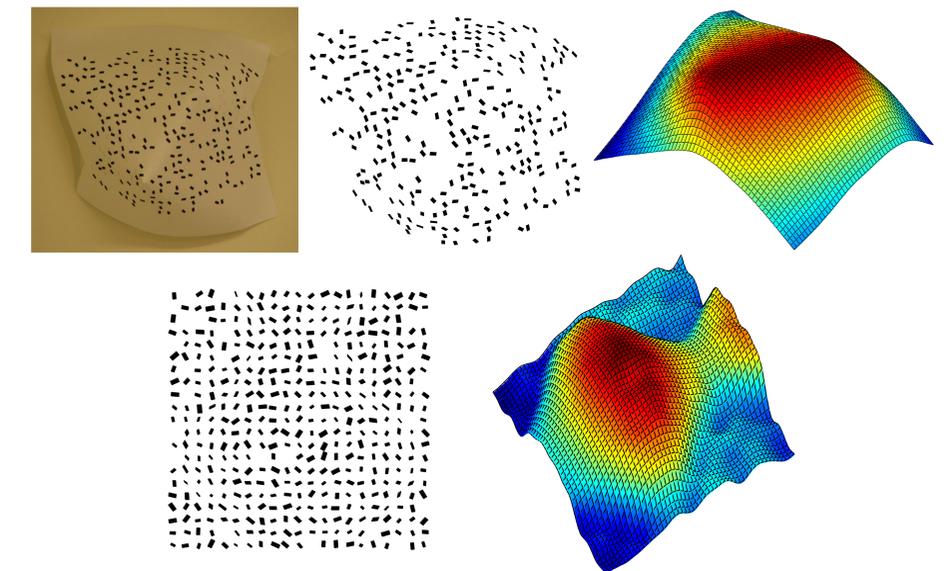
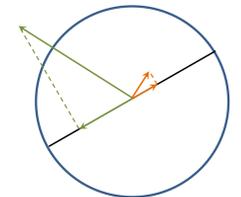
$$X = RR^T, X_{ij} = u_i u_j^T$$

$$\|u_{2i-1}\|^2 + \|u_{2i}\|^2 = 1$$

$$u_{2i-1} \cdot u_{2i} = 0$$

Rounding heuristics

- Scale u_i by the magnitude of the i -th column of X
- Circular sweeps – for each pair of vectors, the smaller projection is considered inactive
- Count the percentage p_i each variable is inactive, and modify the diagonal $C_{ii} = C_{ii} + \mu p_i$
- Solve the modified SDP
- Use K-L for refinement



References

1. Zhu, Q., Shi, J.: Shape from shading: Recognizing the mountains through a global view. In: Proc. CVPR 2006, pp. 1839–1846.
2. Forsyth, D.: Shape from texture and integrability. In: Proc. ICCV 2001, pp. 447–452.
3. Burer, S., Monteiro, R.D.C., Zhang, Y.: Rank-two relaxation heuristics for max-cut and other binary quadratic programs. SIAM J. on Optimization 12(2), pp. 503–521, 2002.