Dynamic Shape Capture via Periodical-illumination Optical Flow Estimation and Multi-view Photometric Stereo

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We presents an optical flow estimation approach which works under periodically varying illuminations, and in cooperation with multi-view photometric stereo, enables high-quality 3D reconstruction of dynamic objects.
Background

Multi-view Stereo + Photometric Stereo = Multi-view Photometric Stereo

Optical Flow Estimation
Our Scheme

Multi-view photometric stereo reconstructs high quality 3D model of moving objects under periodically varying illuminations.
Our Scheme

- The constraints $w_i$ for motion fields [1]
- The locally linear constraint $x_{p,i-1} = x_{p,i} - w_{p,i}$, $x_{p,i+1} = x_{p,i} + w_{p,i}$ (1)
- Recover the real motion vectors $x_{p,i} = x_{k}^{p,i} + dx_{p,i}^{k}$, (2)
- Substituting (2) to (1), we can obtain
  
  $dx_{p,i-1}^{k} - 2dx_{p,i}^{k} + dx_{p,i+1}^{k} = -x_{p,i-1}^{k} + 2x_{p,i}^{k} - x_{p,i+1}^{k}$ (3)

- According to (3), the motion field is recovered via the least squared method.

Our Scheme

- Multi-view Stereo to initialize model
Multi-view Stereo to initialize model [2]

Point Cloud Detection
- Robust Stereo Matching
- Error Point Cleaning
- Frontier and Implicit Point Detection

Point Cloud Merging
- Merging and Down-sampling
- Conflict Point Cleaning

Point Cloud Meshing
- Fidelity based Poisson Surface Reconstruction
- Space Constrained Remeshing

Our Scheme

- Normal Recovery
Our Scheme

- Normal Recovery [3] 
  \[ I_{n \times m} = L_{n \times 9} S_{9 \times m} \]

- Lighting Condition Estimation

- Harmonic Space Optimization

\[ I_j = Ls_j + e \]
\[ \min_{n, \rho} \left\| I_j - Ls_j \right\|_2 \]

\[ I_i = l_i^T S + e \]
\[ \min_{l_i \in \mathbb{R}^9} \left\| I_i - l_i^T S \right\|_1 \]

Our Scheme

- Normal-based Geometric Improvement
Normal-based Geometric Improvement[4]

The MVS can be further optimized by utilizing normal constraints, as the photometric normals can provide the high-frequency detail about the geometry.

We consider both position error and the normal error. The optimization function for the errors consisting of the position $E_p$ and the normal $E_n$ is described as

$$E = \lambda E_p + (1-\lambda) E_n$$

Fig. 1 Warping images under different lighting. (a)(b) The images captured under different illuminations. (c) The interpolated images based on the optical flow estimation between (a) and (b) by [1]. (d) shows the result of warping (a) to (b) by our method.
Experimental Results

Evaluation of the optical flow algorithm

Fig. 2 (a) The model reconstruction based on the linear interpolated images by the optical flow estimation. (b) The model reconstruction based on the linear interpolated images by the proposed optical flow estimation.
Experimental Results

- Compared with MVS

Fig. 3 The high-quality geometry reconstruction for the moving object. (a) The original image. (b) The corresponding geometry model by the MVS. (c) The reconstructed model by our method.
Experimental Results

- Compared with Vlasic et. al. [5, 6]

Fig. 4. The reconstruction by our method and [5].


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Conclusion

Our method

- Reconstructs the high-quality 3D model for moving object
- Optical flow estimation under periodically varying illumination
- Removes the requirement on photometric calibration and the limitation of lighting design

Future work

- fast movement
- occlusion
- reduce computational complexity
Thank You!