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

Ying Fu, Yebin Liu, and Qionghai Dai
Automation Department, Tsinghua University, TNList
fuying.thu@gmail.com, liuyebin@tsinghua.edu.cn, qhdai@tsinghua.edu.cn

Abstract

Multi-view photometric stereo is well established for the shape recovery of static objects. However, it is difficult to align motion images under varying illumination so as to perform photometric stereo reconstruction for dynamic objects. To tackle this issue, this paper presents an optical flow estimation approach which works under periodically varying illuminations, and in cooperation with photometric stereo, enables high-quality 3D reconstruction of dynamic objects. Firstly, multi-view images of the moving object are captured under periodically varying illumination by the multi-camera multi-light system. Then, the optical flow is estimated to synthesize images under different illuminations for each viewpoint. Finally, the multi-view photometric stereo technique is employed to get a high accurate 3D model for each time instant. Experimental results on motion actors demonstrate that temporal successive images under varying illuminations are effectively registered, permitting accurate photometric reconstruction for moving objects.

1. Introduction

3D reconstruction of moving objects is a fundamental problem in realistic modeling for films and games, motion analysis for medical diagnosis and sports science, as well as manufacturing and so on. The development of image based 3D reconstruction techniques has achieved great progress from algorithms to the design of the hardware systems. However, accurate image based 3D reconstruction for moving objects is still one of the most challenging issues, especially for full-body human reconstruction.

Using multiple images of the target object, multi-view stereo (MVS) [1] recovers the dynamic 3D model effectively only for regions containing sufficient texture information, while fails in less textured areas. In contrast, the photometric stereo [2] [3] techniques enable high-quality shape recovery from single viewpoint data, but with unsatisfactory results in merging multi-view normal maps. Therefore, it is expected to combine MVS and photometric stereo to achieve accurate geometric model recovery [4]. However, for moving objects, the photometric stereo method requires multi-illumination images, which are acquired by motion compensation, for each identical action. The performance of motion compensation heavily depends on the optical flow estimation. Consequently, high accurate optical flow estimation under variant illumination is demanded.

Vlasic et al. [5] estimated the optical flow between tracking frames and flowed the other illumination conditions to the tracking frame to obtain the multi-illumination images. They only reconstructed 3D model at capture tracking frame instant. To acquire the high-quality 3D dynamic geometry at each capture instant, we propose an optical flow estimation method under periodically varying illuminations within a multi-camera multi-light system. The reliable optical flow is obtained by an iterative optimization based on a locally linear motion constraint on each three successive frames as well as the constraints on periodical summations of motion filters. Based on the estimated optical flow, motion compensation is performed to synthesize multi-illumination images, required by the photometric stereo, to make a feasible combination of MVS and photometric stereo.

The main contributions of this paper are summarized as...
follows:

- We present a multi-view photometric stereo for high-quality 3D model reconstruction for moving objects under periodically varying illumination.
- We propose an approach to estimate optical flow for unknown periodically varying illuminations.
- We provide a new multi-view multi-illumination dynamic object dataset.

The rest of this paper is organized as follows. Section 2 reviews the related works on optical flow estimation and multi-view photometric stereo. Our capture system is introduced in section 3. The proposed optical flow estimation approach is presented in section 4, and the multi-view photometric stereo for 3D reconstruction in section 5. In section 6, experimental results are provided to illustrate the advantage of the proposed method. Finally, conclusions are drawn in section 7.

2. Related Works

Our method refers to optical flow estimation, MVS and photometric stereo. In the following, we give an overview on relevant works in these fields.

**Optical flow estimation** Optical flow estimation and motion compensation [6, 7] have been investigated in many fields, including frame rate up-conversion [8], stereo reconstruction [9], etc. In particular, the optical flow algorithm has been used in the image alignment [10], motion estimation, and warping [5] between tracking frames (brightness constancy) that are captured by high-speed cameras. It has also been utilized to estimate the scene flow [11] that describes the 3D motion of moving objects. Zhang et al. [12] presented a multi-frame optical flow algorithm under varying illumination, which only focuses on the varying distant illumination that changes moderately for rigid objects.

However, illumination changes significantly in our capture system, since lighting conditions are designed to irradiate different parts of the moving object as much as possible. This breaks the brightness constancy assumption used in conventional optical flow estimation algorithms. To tackle this issue, we propose an iterative algorithm to optimize the optical flow estimation under periodically varying illumination, which can be used for the non-rigid object under extreme illumination variation.

**Multi-view Stereo and Photometric Stereo** Most existing MVS methods utilize the multi-view information based on stereo correlation [14, 15], such as photo-consistency and epipolar geometry. Multi-camera array is usually adopted to capture the motion objects. Bradley et al. [16] established temporally coherent parametrization between incomplete geometry extracted at each capture instant by MVS and then filled holes on the model by templates. Popa et al. [17] captured the low-frequency garment shape by MVS, and then wrinkled the surface based on the estimated folds using space-time deformation to model realistic looking virtual garments.

However, among these MVS methods, a constant illumination condition is assumed and thus the visual cues for reconstruction are insufficient, which greatly limits their ability to recover the high frequency regions on the 3D surface.

In contrast, the photometric stereo [2] technique employs varying illumination and recovers high-quality geometric details in the form of normal maps. But it remains difficult in the merging of multi-view normal maps. In order to obtain high-quality reconstruction, MVS and photometric stereo are combined together, namely multi-view photometric stereo, e.g., [12, 18, 19] adopted a static camera and point light-sources to acquire image sequences of moving objects for reconstructing the 3D model. Vogiatzis et al. [20] and Hernandes et al. [4] captured multi-view images for a moving object under varying illuminations by combining shading and silhouettes. Further more, Higo et al. [21] acquired the multi-view images under varying illumination by a hand-held camera attached with a LED point light to reconstruct a static scene. Wu et al. [22] employ multi-view images under a variety of lights to reconstruct 3D model under uncalibrated illumination.

### Multi-view Photometric Stereo for moving object

Ahmed et al. [23] captured a time-varying scene geometry using the calibrated lighting and multi-view video based on a smooth template. Colored lights are often used in photometric stereo for the dynamic scene. Based on the assumption that the color and reflectance of the object is uniform, Hernández et al. [24] introduced red, green, and blue lights in the sampling system. Decker et al. [25] extended time multiplexing with color multiplexing. Kim et al. [26] adopted time and color illumination multiplexing with three colors. Their optimized implementation ensures constant illumination in one color channel, facilitating optical flow between subsequent frames using standard methods, in spite of illumination changing.

Our work is most related to the work proposed by Vlasic et al. [5], whose system is developed for dynamic shape capture using multi-view photometric stereo. Their method estimates single-view normal by connecting the shading and silhouettes, and then the single view meshes are merged into an entire mesh using a volumetric method. In contrast, our method presents a coarse-to-fine strategy to acquire the normal based on the photometric stereo constraint and the initial model. Then, the geometric model is improved via fusing the recovered normal and the vertex position.

In addition, our method removes the requirement on photometric calibration and the limitation of lighting design.
Meanwhile, the proposed optical flow algorithm not only works on the tracking frames [5], but any successive frames. Therefore, the illumination pattern can be designed arbitrarily in a period, and the geometric model are reconstructed at each capture instant.

3. System Overview

We propose a novel dynamic shape capture method for scenes with periodically changing uncalibrated illumination. In our framework, the required video sequences are captured by a multi-camera and multi-light system (named with dome), as shown in Fig. 2. The shape of the dome system is a hemisphere with a diameter of 6m. There are 20 low speed FLEA2 cameras located on the ring with uniform spacing. The spatial resolution of each image is 1024x768 and the frame rate is 30 FPS. Cameras and LEDs are controlled in synchronization. In this dome, there are 58 individually controllable clusters of light sources, with 10 LEDs in each cluster. The intrinsic and extrinsic camera parameters are calibrated by Zhang et al.’s method [17]. Our method does not require the photometric calibration of 580 LEDs, which is tedious and difficult. Besides, due to the freedom of constraints on the illumination configuration, we can design the periodical illumination arbitrarily as well.

The overall framework of the proposed method is shown in Fig. 2. Firstly, the multi-view multi-illumination video sequences are captured. Then the proposed optical flow estimation approach is used to obtain the multi-light images of each pose for each captured camera view, while the MVS is employed to initialize the normals independently. The multi-light images and the initial normals are combined to recover surface normals precisely. Finally, the recovered normals and geometry position provided by MVS are fused to improve the accuracy of the geometric models. In short, our reconstruction approach includes optical flow based image warping, MVS for model initialization, normal recovery, and geometric model improvement.

4. Optical Flow Estimation

Multi-view video sequences of the moving object are captured in the dome under the varying lighting conditions. At each capture instant, the images are captured under the same lighting condition, but we need the images of the scene with different lighting conditions at each instant, as shown in Fig. 3. The optical flow estimation method under variant lighting conditions is required to interpolate images under multiple lighting conditions for each camera view under each capture instant. In this section, we present an extended optical flow method under variant lighting conditions in detail.

Optical flow is considered as a 2D representation of objects motion. Generally, brightness constancy is assumed, that is to say, the optical flow between the images frames of the moving object meets

\[ I(x, t) = I(x + w, t + 1), \]

where \( I(x, t) \) denotes the intensity of a pixel whose coordi-
nate is \( \mathbf{x} \) at time \( t \), and \( \mathbf{w} \) is the motion vector between images captured at time \( t \) and \( t + 1 \). As the neighboring pixels share similar motions, most of algorithms add the smoothness constraint to the optical flow estimation. The motion vector field is estimated by minimizing the energy function

\[
E(\mathbf{w}) = E_{\text{Data}}(\mathbf{w}) + \alpha E_{\text{Smooth}}(\mathbf{w}),
\]

where \( E_{\text{Data}}(\mathbf{w}) \) and \( E_{\text{Smooth}}(\mathbf{w}) \) describe the brightness constancy and the smoothness of the motion vectors.

The estimated motion vector field is employed to compensate motion and synthesize images with the same pose under different illuminations, so that the photometric normals of the moving object can be reconstructed reliably. However, restricted to the brightness constancy assumption (1), the traditional optical flow methods cannot estimate motion accurately between images when the lighting conditions are rapidly changing, since they tend to erroneously treat the changing light as motion.

Recently, optical flow algorithm proposed by Brox et al. [6] can estimate optical flow accurately under the brightness constancy assumption. Through the introduction of gradient constancy assumption and discontinuity-preserving spatio-temporal smoothness constraint, optical flow estimation under moderately changing illumination is also feasible. However, in our capture system, the designed lighting conditions are supposed to irradiate different parts of the moving subject as much as possible. As a result, variation of brightness could be so significant that traditional optical flow algorithms fail as shown in Fig. 4. Fig. 4(c) shows the result of image warping under different illuminations, where the traditional optical flow estimation fails.

To obtain the optical flow under periodically changing illumination, we apply the locally linear motion constraint on each three successive frames. The linear motion constraint is applied as a prediction of the positions at the previous and next instant. The constraints for motion fields are initialized by conventional optical flow estimation.

Fig. 5 illustrates the optical flow estimation under periodic illuminations. Circles with the same color denote pixels under the same illumination. The constraint optical flow is estimated by the variational approach of Brox et al. [6].

Let \( \mathbf{n} \) denote the number of light patterns within a period, \( p = 1, 2 \) the current and next light period, respectively. The pixel location in the \( i \)-th frame at the \( p \)-th period is represented by \( \mathbf{x}_{p,i} \), and \( \mathbf{w}_{p,i} \) denotes its associated motion vector, where \( i = 1, \cdots, n - 1 \). Assuming a linear motion occurs among three successive frames, the following backward and forward predictions hold,

\[
\mathbf{x}_{p,i-1} = \mathbf{x}_{p,i} - \mathbf{w}_{p,i}, \\
\mathbf{x}_{p,i+1} = \mathbf{x}_{p,i} + \mathbf{w}_{p,i}.
\]

Let \( \mathbf{w}_i \) denotes the motion vector between frames with the same illumination which is recovered using conventional optical flow estimation. Then, we can obtain

\[
\mathbf{x}_{2,i} = \mathbf{x}_{1,i} + \mathbf{w}_i,
\]

where \( \mathbf{x}_{2,i} \) indicates the predicted position of \( \mathbf{x}_{1,i} \) by compensating the estimated motion \( \mathbf{w}_i \). This implicitly pose the constraint on the summation of motion vectors within a period. Then, we employ an iterative algorithm to recover the real motion vectors. Considering the nonlinear motion under the periodically varying illumination, the first order Taylor expansion is used as

\[
\mathbf{x}_{p,i}^{k+1} = \mathbf{x}_{p,i}^k + \frac{\partial \mathbf{x}_{p,i}^k}{\partial \mathbf{x}_{p,i}^{k-1}} d\mathbf{x}_{p,i}^k,
\]

where \( k \) denotes the iteration. To obtain the expansion for \( p = 2 \), the chained differentiation rule is adopted as

\[
d\mathbf{x}_{2,i}^k = \frac{\partial \mathbf{x}_{2,i}^k}{\partial \mathbf{x}_{1,i}^{k-1}} d\mathbf{x}_{1,i}^k.
\]

Substituting (5) into (3), we can obtain

\[
d\mathbf{x}_{p,i}^{k-1} = 2d\mathbf{x}_{p,i}^k + d\mathbf{x}_{p,i}^{k+1} \\
= -\mathbf{x}_{p,i}^{k-1} + 2\mathbf{x}_{p,i}^k - \mathbf{x}_{p,i}^{k+1}
\]

According to (7), the motion field can be recovered via solving the following (overdetermined) linear system

\[
B = AD,
\]
where \( D = [dx_1^k, \cdots, dx_{n-1}^k]^T \), \( B = [-x_1^0 + 2x_1^1 - x_1^2, \cdots, -x_{n-3}^2 + 2x_{n-2}^2 - x_{n-1}^2]^T \), and \( A \) is the coefficient matrix with respect to \( D \). The linear system (8) is solved by the least squared method. The recovered motion field \( D \) is substituted into the (3). Afterward, above procedures are iterated until convergence, i.e., the differentiations \( dx_{p,i} \) approach to zero.

Finally, images with the same pose under different illuminations are warped according to the estimated optical flow. Fig. 4(d) shows the interpolated image by our method. These images are subsequently used to recover the normals for high-quality 3D reconstruction described in section 5.2.

5. Geometric Model Reconstruction

In this section, we first initialize 3D model by MVS. Then, we recover the surface normal by alternating constrained reweighted least absolute values (ACRLAV) algorithm [22]. Finally, the 3D model are improved by fusing the initial normal and the vertex position of the initial model.

5.1. Multi-view Stereo

In this paper, we adopt the point cloud based multi-view stereo algorithm (PCMVS) [13] to initialize the 3D geometric model. PCMVS consists of three main steps: point cloud extraction, merging, and meshing. Firstly, PCMVS extracts point clouds by stereo matching, error point cleaning, and frontier and implicit point detection. Then, the point clouds are merged and conflict points are cleaned. After that, the merged point cloud is meshed by fidelity-based Poisson surface reconstruction and space constrained remeshing.

The reconstructed geometric model offers normals to initialize the 9D harmonic space and correct the low frequency part of photometric normals for the photometric stereo, so that the surface normal can be recovered precisely.

5.2. Normal Recovery

Instead of calibrating light-source, we employ the low order spherical harmonics [28] to represent the general unknown lighting conditions for the Lambertian objects. The multi-view photometric stereo using the second order spherical harmonics approximation to the lighting can be described as

\[
I_{n \times m} = L_{n \times 9} S_{9 \times m},
\]

where \( n \) is the number of lighting patterns, \( m \) is the number of facets. Each row of \( I \) represents the corresponding radiance of the object’s surface under the same lighting condition. Each row of \( L \) is the second order spherical harmonics coefficients for a specific lighting. Each column of \( S \) is the 9D harmonic space of one facet.

As we have obtained the initial model by MVS, the 9D harmonic space can be initialized by its normals. We adopt the ACRLAV [22] for the photometric normals recovery. Firstly, the lighting conditions \( L \) are estimated under the initial normals by solving \( I_i = L S_i \), subject to the minimized absolute errors. With the derived illuminations, the normal for each facet can be acquired by solving \( I_f = L S_f \), subject to the minimized square errors. In practice, the ACRLAV algorithm is iterated 2 to 4 times so as to achieve the accurate surface normals.

Since the cast shadow and the interflection exists in non-lambertian surface, the low-order spherical harmonics approximation is invalid, leading to the erroneous normal estimation. Generally speaking, the low frequency component of the initial normal from the reconstructed geometry by MVS is quite accurate. It can be utilized to correct the low frequency component of the recovered normal by the ACRLAV algorithm. Then, the final normal can be obtained by fusing the initial normal and the recovered normal.

5.3. Normal-based Geometric Improvement

The MVS can be further optimized by utilizing normal constraints, as the photometric normals can provide the high-frequency detail about the geometry. Nehab et al. [29] combine the normal with the geometric position to improve the geometric model. They 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

\[
E = \lambda E^p + (1 - \lambda) E^n,
\]

where \( \lambda \in [0, 1] \) controls the impact strengths of \( E^p \) and \( E^n \) to the optimization function. Here, \( \lambda \) is set to 0.1 in this paper.

6. Experiment results

In this section, we first evaluate the optical flow algorithm. Then, the performance of our algorithm is compared with Vlasic [5] using their public dataset. Finally, we show the results of our algorithm on five models.

The optical flow can be estimated accurately between brightness constancy images. In [5], the optical flow was...
estimated between full-on tracking frames. By assuming a linear motion between tracking frames, the intermediate images under the gradient illumination conditions are flowed to the central tracking frame by linear interpolation. However, this method is suitable for nonlinear motion, for example, twist waist. Fig. 6 compares our method with the linear interpolation used in [5]. They both utilize the variational approach by Brox et al. [6] under the same illumination condition. Fig. 6(c) shows the linear interpolated image based on the optical flow estimation between the images captured under the same illumination. Fig. 6(d) shows the result of warping Fig. 6(a) to Fig. 6(b) by our method. The boxes show the close-up, which demonstrates that our method can estimate the optical flow more accurately than that in [5].

Fig. 7 compares the results of our method and [5] using their public dataset, where (a)(e), (b)(f), and (c)(g) show the original images, results of PCMVS, and results of our method, respectively. Compared with PCMVS, our method reconstructs the model with more details. Fig. 7(d) and (h) show the reconstructed model by [5], which are available on [30]. Because 8 views is too less for the MVS reconstruction method we employed, it is difficult for our method to achieve highly accurate reconstruction with respect to the realistic surfaces. This results in the loss of accuracy in some areas. For areas close to the realistic surfaces, details of textures are well recovered. However, the completeness of our results is considerably better than that of [5] in [30].

Finally, we perform our method on five sequences, including people wearing long skirts, loose clothing, and so on. Each row of Fig. 8 shows the original image, two views of the corresponding reconstructed surface by PCMVS, recovered normal map, and the reconstructed surface by our method. In contrast, our method can recover more detail information, especially for areas with few or no textures, compared with PCMVS.

7. Conclusions and Future Works

We present a novel method for dynamic shape capture via multi-view photometric stereo which is able to reconstruct the high-quality 3D model of moving objects for every captured frame. We introduce a novel optimization scheme for optical flow estimation under the changing illumination, which applies the constraints over both the linearity of local motion and the summation of local motions. Based on the result of optical flow estimation, motion compensation is performed to generate images for the moving object with the same pose under different lighting condition at each view. We also combine the MVS that initializes the geometric model and the photometric stereo to obtain high-quality geometric models.

In the future, we will extend the proposed method to the high-speed camera system. For the optical flow estimation, we expect to introduce the scene flow to estimate the optical flow. According to the MVS, we plan to estimate the occlusion which may offer better optical flow estimation for relevant areas.

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References

Figure 7. The reconstruction by our method and [5]. (a)(e) show the original images. (b)(f) shows the reconstructed model by PCMVS. (c)(g) shows the reconstructed model by our method. (d)(h) shows the result of [5].


Figure 8. Each row shows an original image, the corresponding reconstructed surface by PCMVS, recovered normal map, the reconstructed surface by our method, as well as a novel view of the reconstructed surface by PCMVS, recovered normal map and the reconstructed surface by our method.