



Overview

Scene flow is a dense 3D velocity vector field of a moving and possibly non-rigidly deforming scene. Scene flow finds applications in robotics, UAV's, automotive systems, 4D reconstruction, scientific visualisation

- **Monocular Scene Flow (MSF)** is an emerging standalone field in computer vision
 - **monocular** means that the input is a set of monocular views; **no different views** of the scene corresponding to the same time are available
- Existing MSF methods:
 - extend the classical optical formulation to estimate depths/disparities and 3D motion
 - are limited in handling occlusions and make strong assumptions either on scene or camera motion

	Birkbeck et al. '10 [1]	Birkbeck et al. '11 [2]	Mitche et al. '15 [3]	Xiao et al. '15 [4]	NRSfM-Flow (proposed)
assumptions	known camera motion and constant speed	known proxy geometry of a scene	rigidity, small motion	rigidity, tiny and continuous movements	multiple frames, sufficient motion and deformation
long image sequences	—	—	—	✓	✓
non-rigid scenes	✓	✓	—	—	✓
occlusion handling	—	—	—	estimation on not occluded points (via an "occluded map")	✓

To overcome limitations of previous work, we propose a framework for MSF estimation based on *Non-Rigid Structure from Motion (NRSfM)* techniques - **NRSfM-Flow**

Contributions

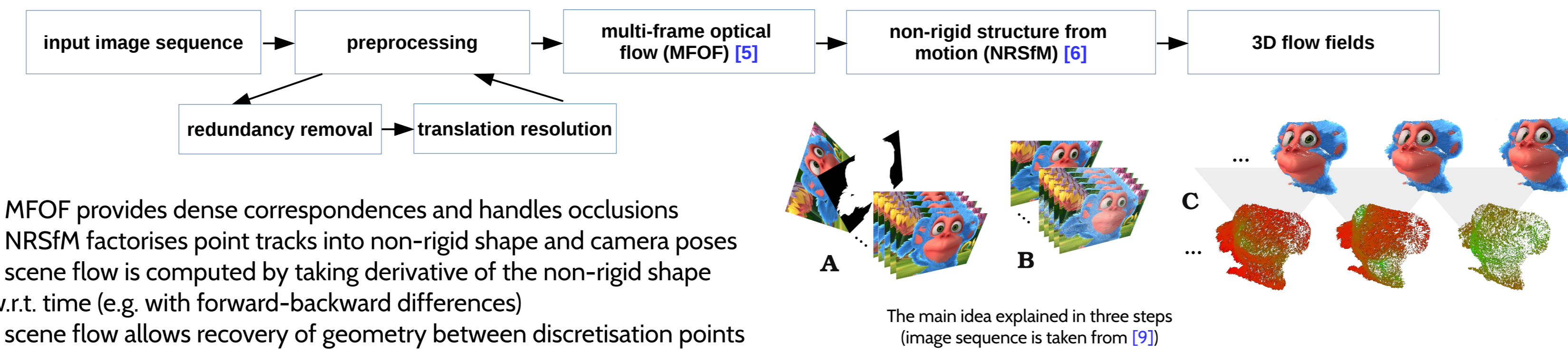
- A novel analytical framework which allows relationship of MSF and NRSfM in the **continuous domain**
- A solution to MSF recovery - **NRSfM-Flow** - based on extensively studied NRSfM under orthographic projection
- Two novel preprocessing steps - **translation resolution** and **redundancy removal** - which broaden the scope of the proposed framework
- NRSfM-Flow combines state-of-the-art methods for correspondence computation and NRSfM
- Draw attention to **model based methods for MSF** and a **differential interpretation of NRSfM**

References

[1] N. Birkbeck, D. Cobzas, and M. Jägersand. Depth and scene flow from a single moving camera. In *3DPVT*, 2010.
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 [6] R. Garg, A. Roussos, and L. Agapito. Dense variational reconstruction of non-rigid surfaces from monocular video. In *CVPR*, pp. 1272-1279, 2013.
 [7] D. J. Butler, J. Wulff, G.B. Stanley, G. B. and M.J. Black. A naturalistic open source movie for optical flow evaluation. In *ECCV*, 2012.
 [8] P. Dinning. Barn Owl at Screech Owl Sanctuary. <https://www.youtube.com/watch?v=xmou8t-DHh0>, [online; accessed on 12.05.2016; usage rights obtained], 2014.
 [9] N. Mayer, E. Ilg, P. Hausser, P. Fischer, D. Cremers, A. Dosovitskiy, T. Brox. A Large Dataset to Train Convolutional Networks for Disparity, Optical Flow, and Scene Flow Estimation. In *CVPR*, 2016.

NRSfM-Flow

The main idea:

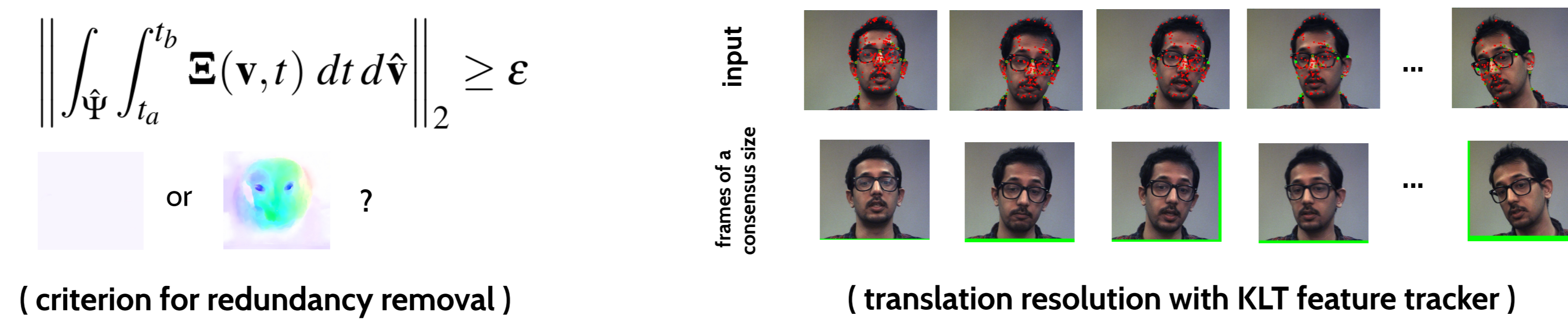


NRSfM-Flow equations: relation between NRSfM and MSF in the continuous domain

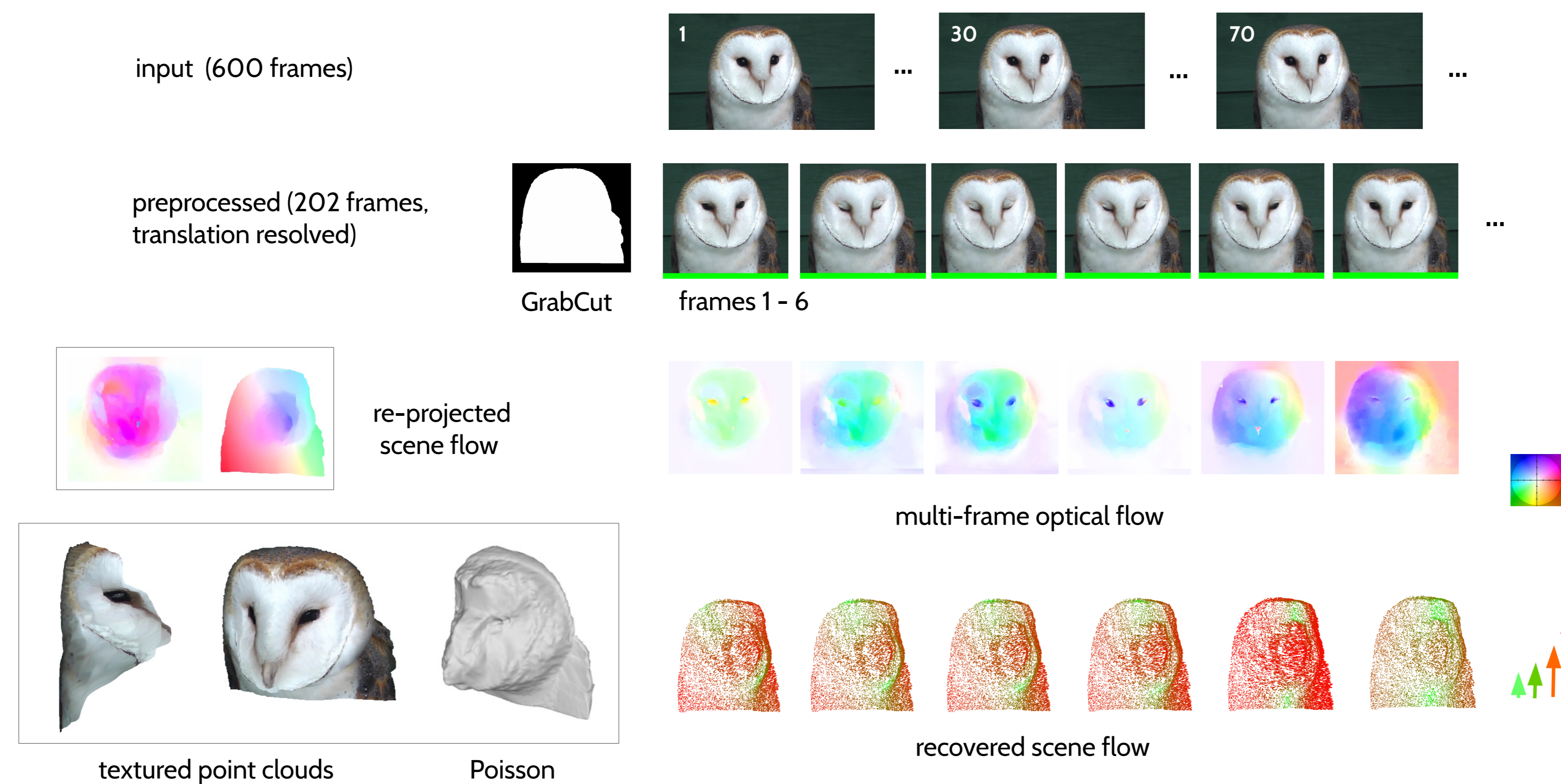
$$\begin{aligned}
 \text{I} \quad \mathbf{W}(\hat{\mathbf{v}}, t) &= \mathbf{W}_\tau(\hat{\mathbf{v}}, t) + \mathbf{C}(\hat{\mathbf{v}}) = \mathbf{R}(t) \mathbf{S}(\mathbf{p}, t) & \text{IV} \quad \mathbf{W}_\tau(\hat{\mathbf{v}}, t) &= \int_\tau^t \mathbf{\Xi}(\hat{\mathbf{v}}, t) dt \\
 \text{II} \quad \Theta(\mathbf{p}, t) &= \frac{\partial \mathbf{R}(t)}{\partial t} \mathbf{S}(\mathbf{p}, t) + \mathbf{R}(t) \frac{\partial \mathbf{S}(\mathbf{p}, t)}{\partial t} & \text{V} \quad \int_\tau^t \mathbf{\Xi}(\hat{\mathbf{v}}, t) dt + \mathbf{C}(\hat{\mathbf{v}}) &= \mathbf{R}(t) \mathbf{S}(\hat{\mathbf{p}}, t) \\
 \text{III} \quad \Theta(\mathbf{p}, t) &= \frac{\partial \mathbf{S}(\mathbf{p}, t)}{\partial t} & \text{VI} \quad \mathbf{\Xi}(\hat{\mathbf{v}}, t) &= \mathbf{R}_{2 \times 3}(t) \frac{\partial \mathbf{S}(\hat{\mathbf{p}}, t)}{\partial t}
 \end{aligned}$$

domain	meaning	defined notions
$\mathbf{p} \in \Omega \subset \mathbb{R}^{3+1}$	all 3D points of a scene	3D scene $\mathbf{S}(\mathbf{p}, t)$, scene flow $\Theta(\mathbf{p}, t)$
$\hat{\mathbf{p}} \in \hat{\Omega} \subset \mathbb{R}^3$	reconstructed 3D points	reconstructed 3D surface $\mathbf{S}(\hat{\mathbf{p}}, t)$
$\mathbf{v} \in \Psi \subset \mathbb{R}^{2+1}$	all observed 2D points	images $\mathbf{I}(\mathbf{v}, t)$, optical flow $\mathbf{\Xi}(\mathbf{v}, t)$
$\hat{\mathbf{v}} \in \hat{\Psi} \subset \mathbb{R}^2$	2D points visible at time τ	measurement function $\mathbf{W}_\tau(\hat{\mathbf{v}}, t)$

Preprocessing steps in NRSfM-Flow



Example: barn owl sequence [8] uncompressed (input) and compressed (preprocessed)



Experiments

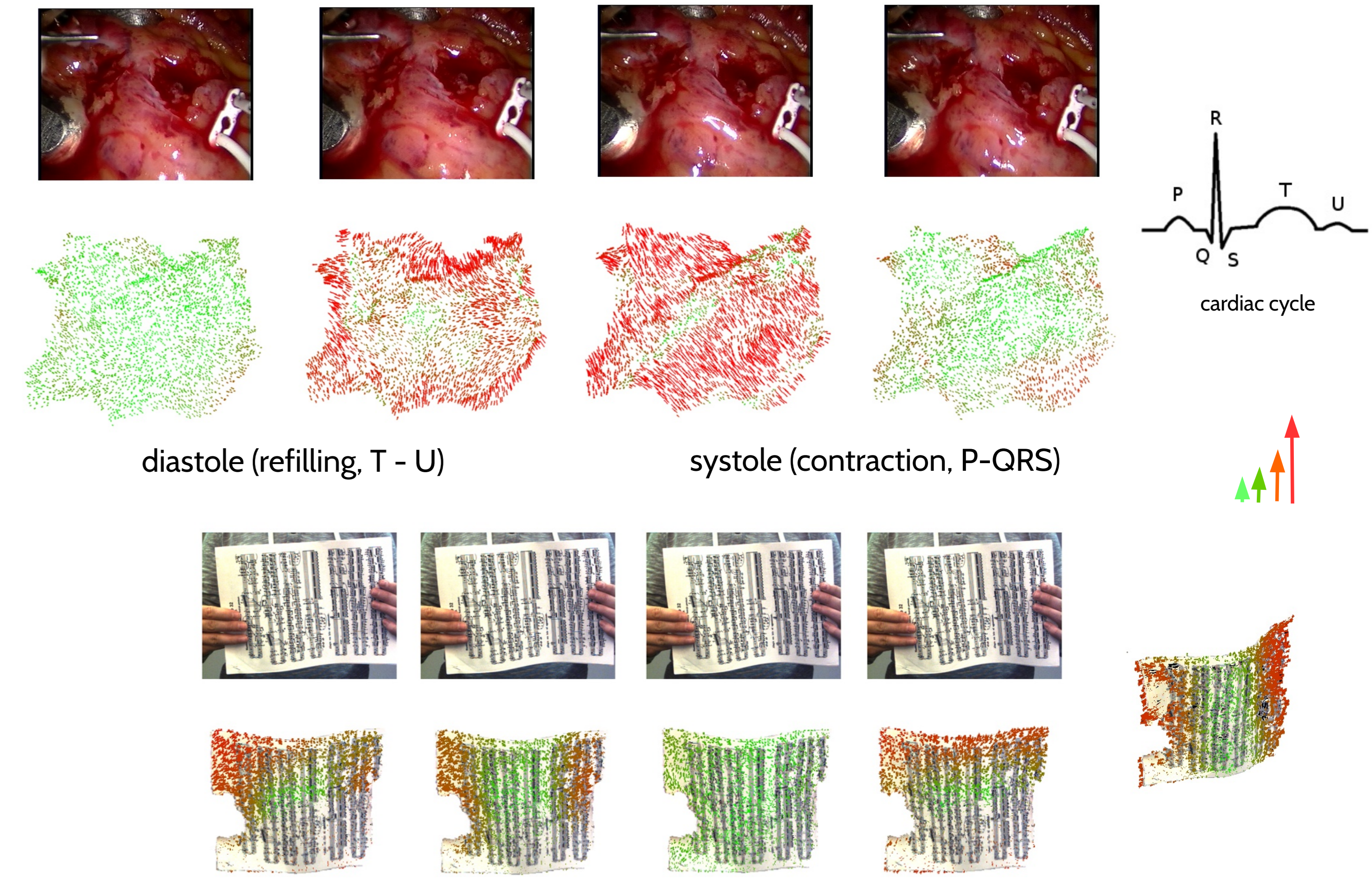


Figure 1. Results on the heart and music notes (L. v. Beethoven's 32 Sonata notes bending) sequence. NRSfM-Flow allows to better visualize reconstructed geometry and deformations which can not be perceived well from a single perspective/angle of view.

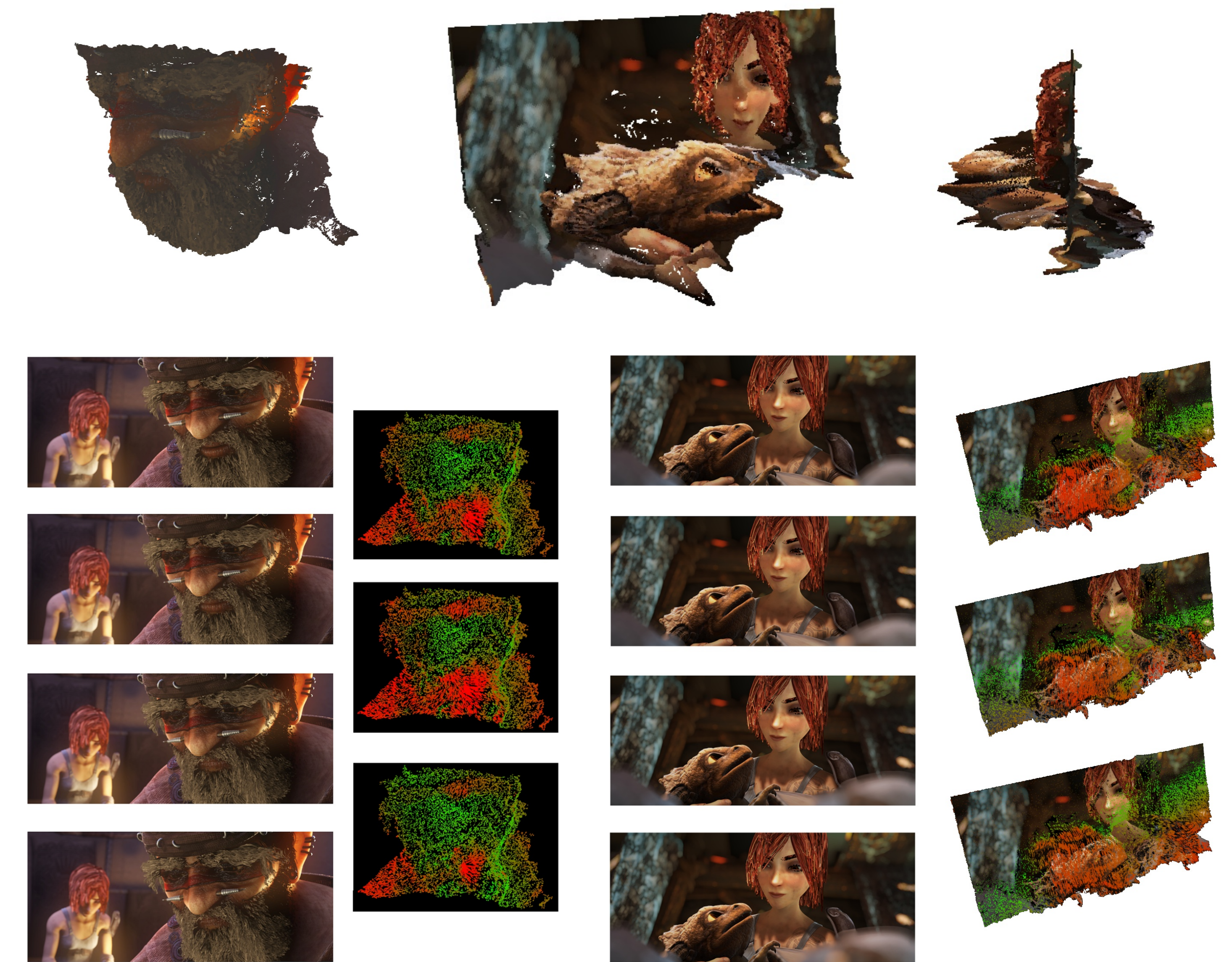


Figure 2. Results on the SINTEL [7] shaman2 and bangade2 sequences. Due to an orthographic NRSfM, the proposed framework cannot recover relative depths of objects in a complex orientation. Taking into account perspective distortions could improve results and is a part of future work. NRSfM-Flow will benefit from progress in the area of NRSfM.