High-Accuracy Camera Calibration and Scene Acquisition

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Presentation Outline

- Unconstrained imaging model
  - Calibration

    Filippo Bergamasco, Andrea Albarelli, Emanuele Rodola, Andrea Torsello
    Can a Fully Unconstrained Imaging Model Be Applied Effectively to Central Cameras?
    IEEE Conference on Computer Vision and Pattern Recognition, IEEE, pp. 1391-1398, CVPR, 2013.
  - Rays interpolation

    Andrea Albarelli, Cosmo Luca, Filippo Bergamasco, Andrea Torsello
    High-Coverage 3D Scanning through Online Structured Light Calibration
    22nd International Conference on Pattern Recognition, pp.4080-4085, ICPR, 2014.
  - Central model with unconstrained distortion

    Filippo Bergamasco, Luca Cosmo, Andrea Gasparetto, Andrea Albarelli, Andrea Torsello
    Non-Parametric Lens Distortion Estimation for Central Cameras
    UNDER REVIEW, CVPR, 2015.
- Simultaneous Flow and Dichromatic model recovery

  Filippo Bergamasco, Antonio Robles-Kelly, Andrea Torsello
  Dichromatic Parameter Recovery from Two Views via Total Variation Hyper-priors
  UNDER REVIEW, CVPR, 2015.

Additional topics covered in the thesis

- Fiducial markers

  Filippo Bergamasco, Andrea Albarelli, Andrea Torsello
  Pi-Tag: a fast image-space marker design based on projective invariants
  Machine Vision and Applications (ISSN:0932-8092), pp. 1295- 1310, MVA, 2013.

- Calibration with circular features

  Filippo Bergamasco, Andrea Albarelli, Luca Cosmo, Emanuele RodolÃă, Andrea Torsello
  RUNE-TAG: an Accurate and Robust Artificial Marker based on Cyclic Codes
  UNDER REVIEW, PAMI, 2013.

- Multi-View 3D Ellipse estimation

  Filippo Bergamasco, Luca Cosmo, Andrea Albarelli , Andrea Torsello
  A Robust Multi-Camera 3D Ellipse Fitting for Contactless Measurements
  2nd Joint 3DIM/3DPVT Conference 3D Imaging, Modeling, Processing, Visualization, Transmission, IEEE, pp. 168- 175., 2012.

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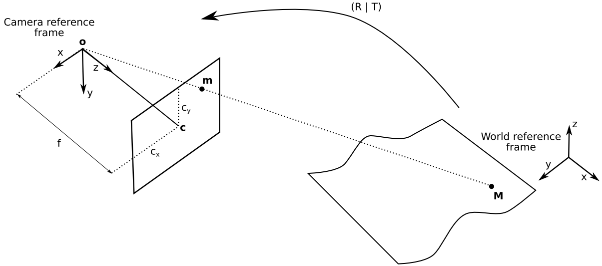
Unconstrained imaging model

Unconstrained imaging model
Introduction

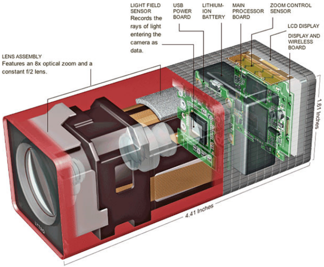
Pinhole model (with distortion) is widely adopted

- Approximates well the behaviour of common cameras
- Excellent trade-off between the number parameters to estimate and its accuracy



Unconstrained imaging model
Introduction

Different optical setups exist demanding ad-hoc camera models

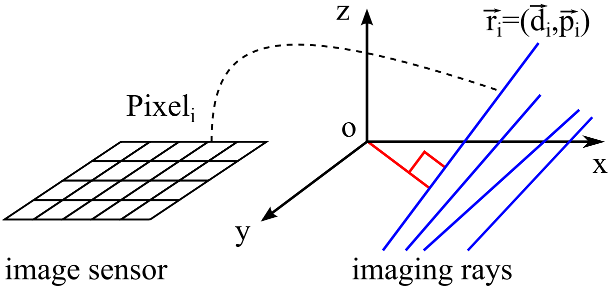


Unconstrained imaging model

Introduction

In the most general case, we can think of a **Fully-unconstrained imaging model**

- Each pixel (basic light sensor) is associated to a 3D straight line (**ray**)
- Each ray is independent with respect to the others



4 dof for each ray, assuming $\vec{d}_i^T \vec{p}_i = 0, \|\vec{d}\| = 1$

Unconstrained imaging model

Introduction

Many advantages:

- No constraints on optical path geometry
- Can accommodate very complex lens setups

Key problem

Comprises literary millions of free parameters to estimate

- Common calibration targets fail to provide enough data
- Optimization procedure too slow
- Methods exist in literature comprising complicated calibration setups

Question:

What if we try to use such model on a quasi-pinhole camera?

Unconstrained imaging model

For pinhole cameras?

At first sight, it seems a nonsense! But...

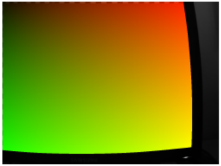
- Are we sure that radial distortion can describe properly the lens inner working?
- Is the camera really pinhole?
- It would be interesting to have a single general model to describe a broad range of different cameras

Key contributions/novelties:

1. We propose an effective technique to calibrate an unconstrained camera model
2. We show that such model can achieve better results than the pinhole
3. We propose a technique to interpolate camera rays
4. We propose a variation of the method to obtain a central model with unconstrained distortion

Unconstrained imaging model
Calibration

Standard point-based calibration targets simply cannot provide enough data to estimate the huge number of parameters



We solve this problem by providing a dense localization of the target obtained via structured-light patterns shown on a normal LCD display

- Phase coding with the number-theoretical phase unwrapping approach
- We encode horizontal and vertical pixel coordinates of each pixel
- High precision **sub-pixel** localization of the target coordinates of each ray

Unconstrained imaging model
Calibration

Target is acquired in s different poses $\Theta_s = (R_s, \vec{t}_s)$, $R_s = (\vec{u}_s \vec{v}_s \vec{n}_s)$.
For each pose and ray, we have

- The observed code $\mathbf{Co}_i^s \in \mathbb{R}^2$
- The expected code
  $\mathbf{Ce}(\vec{r}_i|\Theta_s) = (\vec{u}_s \vec{v}_s)^T \left(\frac{\vec{n}_s^T(\vec{t}_s - \vec{p}_i)}{\vec{n}_s^T \vec{d}_i} \vec{d}_i + (\vec{p}_i - \vec{t}_s) \right)$

We express the calibration process as a generalized least squares problem

$$(\hat{\vec{r}}, \hat{\Theta}) = \operatorname*{argmin}_{\vec{r}, \Theta} \sum_{i,s} (\varepsilon_i^s)^T (\Sigma_i^s)^{-1} \varepsilon_i^s$$

where $\varepsilon_i^s = \mathbf{Co}_i^s - \mathbf{Ce}(\vec{r}_i|\Theta_s)$ are the code residuals and Σ_i^s is the (conditional) error covariance matrix under the given pixel-pose combination.

Unconstrained imaging model
Calibration

Main Result

The generalized least squares formulation with respect to the target coordinates corresponds to the standard **linear least squares** with respect to the 3D points associated with each ray (details in the thesis).

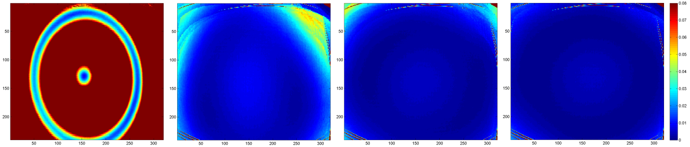
We take advantage by the independence between rays and poses

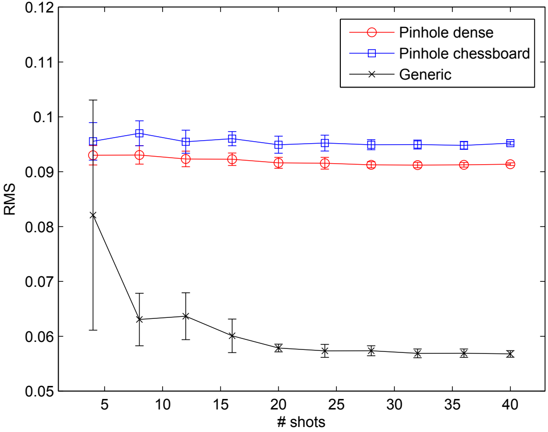
Two step optimization process

- Each ray is optimized by considering the poses fixed (lls)
- Each pose is optimized by considering the rays fixed (Point-line ICP)

Unconstrained imaging model

Optimization results





Unconstrained imaging model

Using the model

One reason that makes pinhole model effective is that exists a continuous mapping between any point (u, v) and the corresponding ray exiting the camera.

- 3D point triangulation performed by searching correspondences
- Epipolar geometry is available
- Dense stereo, etc.

In the unconstrained model we just have a **sparse bundle of rays in space**.

Problem:

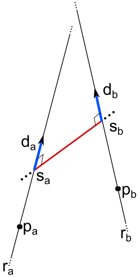
To triangulate rays and perform 3D reconstruction we need an **interpolation** function to estimate the ray associated to a given point in the image plane

- We assume some sort of smoothness in the bundle indexed by the image lattice

Unconstrained imaging model
Rays interpolation

Let $R_d = \{\vec{r}_i\}$ a set of n known camera rays, and $\vec{w} = (w_1, \ldots, w_n) \in \mathbb{R}^n, \sum_{i=1}^{n} w_i = 1$ a convex combination of weights.

Given two rays $\vec{r}_a, \vec{r}_b$, we define the best rigid motion interpolant K_{ab} as the combination of:



1. The rotation R_K around the axis $\vec{d}_a \times \vec{d}_b$ with angle $\mathrm{acos}(\vec{d}_a^T \vec{d}_b)$
2. The translation $T_K = \vec{s}_b - \vec{s}_a$, with $\vec{s}_a$ and $\vec{s}_b$ being the two rays nearest points

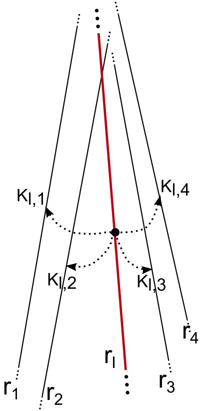
By describing each motion K_{ab} in terms of a screw motion represented via dual-quaternions, we pose rays interpolation in terms of **rigid motions blending**

Unconstrained imaging model

Rays interpolation algorithm

Initailize the interpolated ray $\vec{r}_\ell = (\vec{d}_\ell, \vec{p}_\ell)$ as a weighted linear combination followed by a reprojection on the rays manifold:

$$\vec{d}_\ell = \frac{\sum_{i=1}^{n} w_i \vec{d}_i}{||\sum_{i=1}^{n} w_i \vec{d}_i||}, \vec{p}_\ell = \frac{\sum_{i=1}^{n} w_i \vec{p}_i}{||\sum_{i=1}^{n} w_i \vec{d}_i||} - \vec{d}_\ell \left(\vec{d}_\ell^T \frac{\sum_{i=1}^{n} w_i \vec{p}_i}{||\sum_{i=1}^{n} w_i \vec{d}_i||} \right)$$



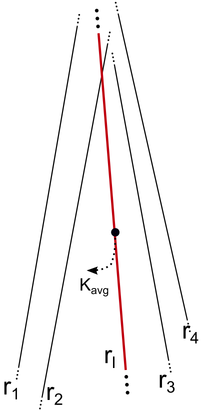
1. Compute $K_{\ell,i=1\ldots n}$ as the screw motion between $\vec{r}_\ell$ and $\vec{r}_i$

Unconstrained imaging model

Rays interpolation algorithm

Initailize the interpolated ray $\vec{r}_\ell = (\vec{d}_\ell, \vec{p}_\ell)$ as a weighted linear combination followed by a reprojection on the rays manifold:

$$\vec{d}_\ell = \frac{\sum_{i=1}^{n} w_i \vec{d}_i}{|| \sum_{i=1}^{n} w_i \vec{d}_i ||}, \vec{p}_\ell = \frac{\sum_{i=1}^{n} w_i \vec{p}_i}{|| \sum_{i=1}^{n} w_i \vec{d}_i ||} - \vec{d}_\ell \left(\vec{d}_\ell^T \frac{\sum_{i=1}^{n} w_i \vec{p}_i}{|| \sum_{i=1}^{n} w_i \vec{d}_i ||} \right)$$



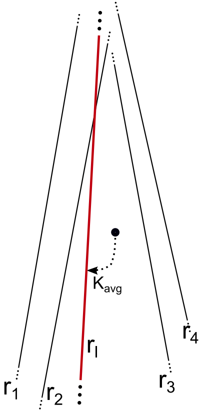
1. Compute $K_{\ell,i=1\ldots n}$ as the screw motion between $\vec{r}_\ell$ and $\vec{r}_i$
2. Perform *Dual-quaternion Iterative Blending* algorithm to obtain K_{avg}

Unconstrained imaging model

Rays interpolation algorithm

Initailize the interpolated ray $\vec{r}_\ell = (\vec{d}_\ell, \vec{p}_\ell)$ as a weighted linear combination followed by a reprojection on the rays manifold:

$$\vec{d}_\ell = \frac{\sum_{i=1}^n w_i \vec{d}_i}{||\sum_{i=1}^n w_i \vec{d}_i||}, \vec{p}_\ell = \frac{\sum_{i=1}^n w_i \vec{p}_i}{||\sum_{i=1}^n w_i \vec{d}_i||} - \vec{d}_\ell \left(\vec{d}_\ell^T \frac{\sum_{i=1}^n w_i \vec{p}_i}{||\sum_{i=1}^n w_i \vec{d}_i||} \right)$$



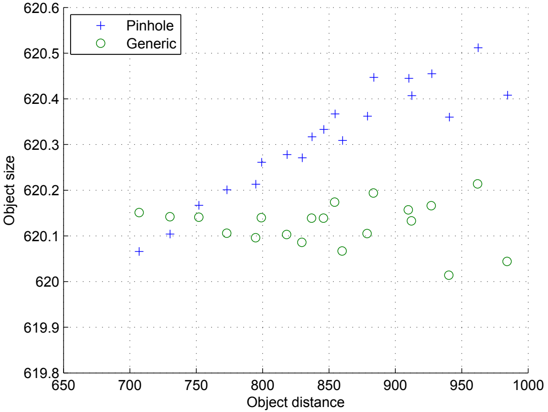
1. Compute $K_{\ell, i=1 \dots n}$ as the screw motion between $\vec{r}_\ell$ and $\vec{r}_i$
2. Perform *Dual-quaternion Iterative Blending* algorithm to obtain K_{avg}
3. Apply K_{avg} to $\vec{r}_\ell$
4. Return to step 1 and iterate until convergence

Unconstrained imaging model

Stereo triangulation experiment

We tested the performance of the unconstrained model for stereo triangulation.

- Stereo RT computed via the same point-rays ICP
- As interpolation weights we used the inverse of the squared distances of 8 neighbours



Pinhole model with unconstrained distortion
Introduction

- We demonstrated the effectiveness of the unconstrained model even for quasi pinhole cameras
- Many classical computer vision techniques heavly rely on the epipolar geometry given by central projection
- We believe that most of the improvements exhibited by the unconstrained model are due to a better **lens distortion** accommodation

Proposed tradeoff:

Fall-back to a **central** model but allowing a complete **unconstrained distortion**

Pinhole model with unconstrained distortion

Calibration process

The calibration process starts from estimate the bundle of camera rays

- Alternating optimization of rays assuming fixed poses, viceversa
- Pose estimation step exactly as before
- Rays optimization step slightly more complicated as it must estimate the common optical center o

Since rays are all forced to pass trough o, they are parametrized just by a vector $d_i \in \mathbb{R}^3, \|d\| = 1$

$$(\hat{\vec{d}}, \hat{\Theta}, \hat{o}) = \operatorname*{argmin}_{\vec{d}, o, \Theta} \sum_{i,s} (\varepsilon_i^s)^T (\Sigma_i^s)^{-1} \varepsilon_i^s$$

Pinhole model with unconstrained distortion
Rays and optical center calibration step

Let $\mathbf{x}^s_{(u,v)} = RT_s \begin{pmatrix} \mathbf{Co}^s_{(u,v)} & 0 & 1 \end{pmatrix}^T$ be the 3D coordinates of the observed code $\mathbf{Co}^s_{(u,v)}$ transformed trough the pose RT_s.

We can formulate the estimation of o as:

$$\underset{o}{\operatorname{argmin}} \sum_{u,v} \min_{d_{(u,v)}} \sum_{s} \|(h^s_{(u,v)})^T (I - d_{(u,v)} d^T_{(u,v)})\|^2$$

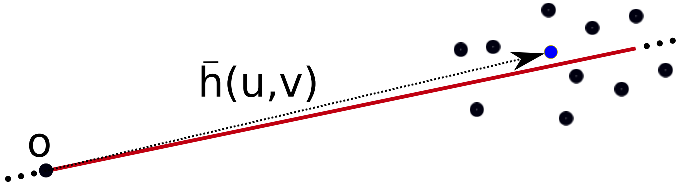
Where $h^s_{(u,v)} = (\mathbf{x}^s_{(u,v)} - o)$.

Key result

Under the assumption that the distance between each ray and its expected code is small, this can be transformed in term of the **point clouds** generated by the intersection of a ray and each target pose

Pinhole model with unconstrained distortion

Rays and optical center calibration step



$$\underset{o}{\operatorname{argmax}} \sum_{u,v} N_{(u,v)} \frac{\bar{h}^T_{(u,v)} \mathbf{S}_{(u,v)} \bar{h}_{(u,v)}}{\|\bar{h}_{(u,v)}\|^2}$$

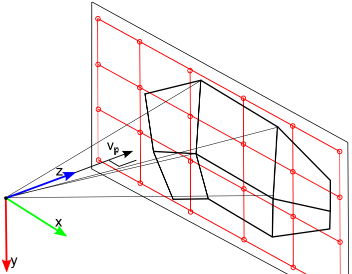
- $\mathbf{S}_{(u,v)}$ Covariance of the point cloud
- $N_{(u,v)}$ number of points in the cloud
- $\bar{h}_{(u,v)}$ is the vector connecting o and the cloud centroid

The functional is further rewritten to be solved as a fixed point iteration

Pinhole model with unconstrained distortion
Estimating a new virtual pinhole

After ray bundle recovery we create a **virtual pinhole camera**. We need to estimate:

- Image plane orientation and distance
- The undistortion mapping to obtain a regular grid

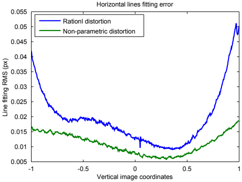


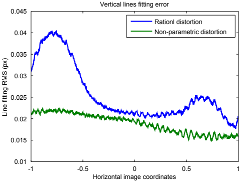
- plane orientation minimizing the variance of distances between each plane-ray intersection point
- points topology inherited by image lattice
- points resampled in a uniform grid to compute the undistortion function
- value at each grid point as function of 4 neigh.

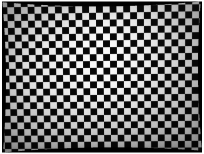
Pinhole model with unconstrained distortion

Results

Better radial distortion correction:

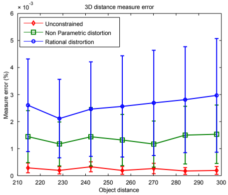


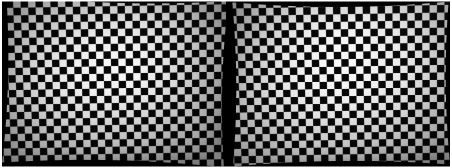




An unified model for mono and stereo cameras

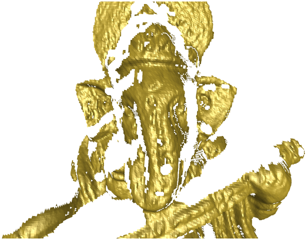
Stereo cameras can be seen as a unique bundle of rays with an undistortion function that rectifies epopolar lines





Pinhole model with unconstrained distortion
Results

Better and fast 3D reconstruction trough dense stereo



OpenCV Undistort+Rectify

Proposed method

Conclusions

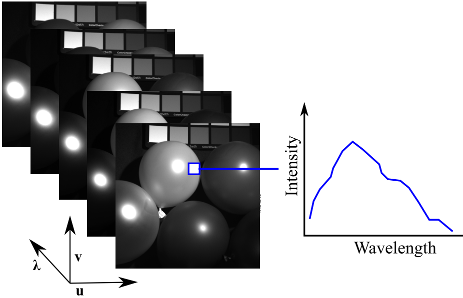
- We proposed an effective calibration technique for a fully unconstrained camera model
- We demonstrated its advantages even for quasi pinhole cameras
- We proposed a method to create virtual pinhole cameras with model-free distortion functions
  - Very effective also for stereo rigs

Simultaneous Optical Flow and Dichromatic Parameters Recovery

Flow and Dichromatic parameters recovery
Introduction

- We usually see cameras as a grid of simple photons collectors disposed in a grid.
- When we start discriminating on light frequency, we enter the field of Multi-Spectral imaging
- RGB camera is a multi-spectral device with just 3 bands

- Data cube representation
- Multi-spectral data leverage the analysis to physical properties of materials



Flow and Dichromatic parameters recovery
Introduction

We assume a uniform illuminant spectrum

Dichromatic Model

Expresses the image radiance $I(\mathbf{u}, \lambda)$ at pixel location $\mathbf{u} = (u_1, u_2)$ and wavelength λ as:

$$I(\mathbf{u}, \lambda) = g(\mathbf{u})L(\lambda)S(\mathbf{u}, \lambda) + k(\mathbf{u})L(\lambda)$$

- I is the "cube" measured by the camera
- g is the shading. Depends by **geometry**
- S is the reflectance. Depends by **material**
- L is the illuminant
- k is a specular factor

Flow and Dichromatic parameters recovery
Introduction

In literature there exist different approaches to factorize S, L, g and k given a single radiance image I.

Reflectance is particularly interesting being invariant to the object geometry and its relative position wrt. the viewer

- Is preserved across **multiple images** of the scene

Novelties of the proposed approach

1. The first two-views dichromatic model recovery method
2. We developed a novel affine hyper-prior combined with a TV regularizer

Flow and Dichromatic parameters recovery

Problem formulation

Two input irradiance images of the same scene are given: $I_1(\mathbf{u},\lambda), I_2(\mathbf{u},\lambda)$

An optical flow function $f(\mathbf{u}) = \mathbf{u}' : \Omega_1 \rightarrow \Omega_2$ maps points from the first to the second image

The "constant brightness assumption" is not valid for highly specular pixels

- Brightness strongly dependent on the relative angle between the observer and the light

We make use of the multiplicative gating function

$$W(\mathbf{u}) = \exp\left(-\tau || I(\mathbf{u},\lambda) - \mathcal{P}(I(\mathbf{u},\lambda)) ||\right)$$

where $\mathcal{P}(I(\mathbf{u},\lambda))$ is the projection of the image radiance $I(\mathbf{u},\lambda)$ onto the dichromatic plane.

Flow and Dichromatic parameters recovery
Problem formulation

We defined two energy terms measuring the coherency of the recovered dichromatic model and flow with the input data

$$E_{\mathrm{DI}_1} = \int_{\Omega_1} W_1(\mathbf{u})^2 \sum_{\lambda} \Big(I_1(\mathbf{u},\lambda) - L(\lambda)\Big(g_1(\mathbf{u}) S(\mathbf{u},\lambda) + k_1(\mathbf{u})\Big)\Big)^2 d\mathbf{u}$$

$$E_{\mathrm{DI}_2} = \int_{\Omega_1} W_2(\mathbf{u}')^2 \sum_{\lambda} \Big(I_2(\mathbf{u}',\lambda) - L(\lambda)\Big(g_2(\mathbf{u}') S(\mathbf{u},\lambda) + k_2(\mathbf{u}')\Big)\Big)^2 d\mathbf{u}$$

Note

Due to the gating functions, the evaluation is performed only on non specular areas. Hence, the contribution of k_1 and k_2 is negligible

Flow and Dichromatic parameters recovery
Problem formulation

We pose the problem as the minimization of the energy functional:

$$\operatorname*{argmin}_{f,S,L,g} \left(\mu E_{\mathrm{DI}_1} + (1-\mu) E_{\mathrm{DI}_2} \right)$$

The problem is highly under-determined. The flow function itself allows many different solutions.

A common approach is to use a regularizer enforcing a certain degree of smoothness in the solution

- Many different regularizers proposed over the last decades
- Aim: Preserve edges, possibly implying physical/meaninful constraints

Flow and Dichromatic parameters recovery

Total Variation regularizer

Let f be a differentiable function. The Total Variation (TV) of f is defined as:

$$\mathrm{TV}(f) = \int_{\Omega} ||Df(x)||_2 \, dx$$

Main property

Used as a regularizer, TV privileges piecewise constant solutions.

Unfortunately, the regularized optimization problem

$$\min_{f} E(f) + TV(f)$$

is not convex. We switch to the relaxed problem:

$$\min_{f, f_{\mathrm{TV}}} E(f) + \int \frac{||f - f_{\mathrm{TV}}||^2}{\delta} + TV(f_{\mathrm{TV}})$$

Flow and Dichromatic parameters recovery
Optical Flow parametrization

Using a TV regularizer is a natural choice for S

- We expect large areas of the same material

However, it does not make sense to impose piecewise constant flow parametrized as displacements on the image plane

Key contribution

We use a higher order smoothness prior, where the displacement is assumed to be locally affine:

$$f(\mathbf{u}) = \mathbf{u} + A(\mathbf{u})\mathbf{u} = \begin{pmatrix} u \\ v \\ 1 \end{pmatrix} + \begin{pmatrix} a_1(\mathbf{u}) & a_2(\mathbf{u}) & a_3(\mathbf{u}) \\ a_4(\mathbf{u}) & a_5(\mathbf{u}) & a_6(\mathbf{u}) \\ 0 & 0 & 0 \end{pmatrix} \begin{pmatrix} u \\ v \\ 1 \end{pmatrix}$$

Approximates view transformation under a weak camera model of **local planar patches**.

Flow and Dichromatic parameters recovery
Optimization

$$
\begin{aligned}
E = & \ \alpha \left(\mu E_{\mathrm{DI}_1} + (1-\mu) E_{\mathrm{DI}_2} \right) \\
& + \rho_S \left(\int_{\Omega_1} \frac{||S(\mathbf{u}) - S_{\mathrm{TV}}(\mathbf{u})||^2}{\delta_S} \, d\mathbf{u} + \int_{\Omega_1} ||DS_{\mathrm{TV}}(\mathbf{u})||_2 \, d\mathbf{u} \right) \quad (1) \\
& + \rho_f \left(\int_{\Omega_1} \frac{||A(\mathbf{u}) - A_{\mathrm{TV}}(\mathbf{u})||_2^2}{\delta_f} \, d\mathbf{u} + \int_{\Omega_1} ||DA_{\mathrm{TV}}(\mathbf{u})||_2 \, d\mathbf{u} \right) \quad (2)
\end{aligned}
$$

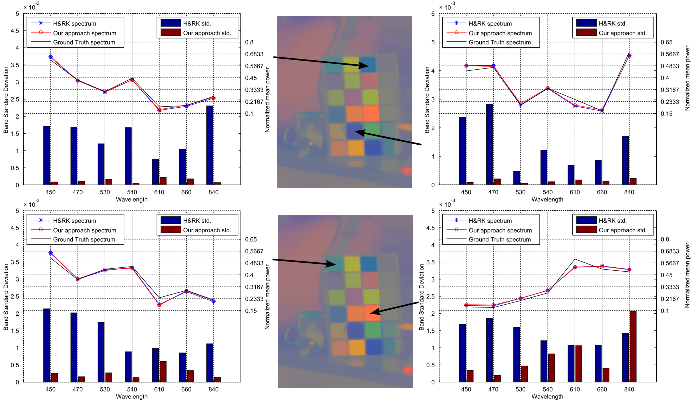
which is minimized over S, f, L, g_1, g_2, S_{TV}, and f_{TV}.

Alternating minimization

1. Minimize with respect to $L(\lambda)$, $g_1(\mathbf{u})$, and $g_2(f(\mathbf{u}))$, keeping $S(\mathbf{u},\lambda)$, $f(\mathbf{u})$, $S_{\mathrm{TV}}(\mathbf{u},\lambda)$ and $A_{\mathrm{TV}}(\mathbf{u})$ fixed;
2. Update $S(\mathbf{u},\lambda)$ and $f(\mathbf{u})$ through a gradient descent step, keeping all other variables fixed;
3. Minimize (1) and (2) to obtain a new estimate of $A_{\mathrm{TV}}(\mathbf{u})$ and $S_{\mathrm{TV}}(\mathbf{u})$.

Flow and Dichromatic parameters recovery
Results

- For our tests we used a multi-spectral device delivering 6 channels in visible spectrum and one in the near-infrared
- We compare with the current industrial-grade state-of-the-art



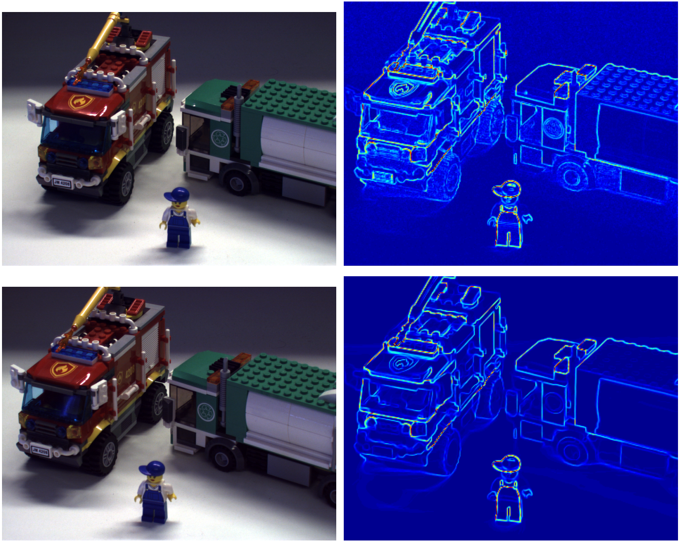
Our approach shows less std. and better reflectance recovery

Flow and Dichromatic parameters recovery

Qualitative Results

Input　　　　Reflectance

Flow and Dichromatic parameters recovery
Qualitative Results



Input

Reflectance norm

Flow and Dichromatic parameters recovery
Qualitative Results

Input Flow norm

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Conclusions

- We proposed a novel technique to simultaneously recover the optical flow and dichromatic parameters from two-views
- Our method encompass the current state-of-the-art delivering a better factorization of dichromatic components
- The novel affine hyper-parior combined with a TV regularizer provides a natural piecewise-rigid assumption on the motion under a weak camera model
- The TV regularized for reflectance impose local patches of uniform material
- We are currently working on a novel homographic hyper-prior

Thank you for your attention

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Published Papers

- FILIPPO BERGAMASCO, ANDREA ALBARELLI, EMANUELE RODOLA, ANDREA TORSELLO

  Can a Fully Unconstrained Imaging Model Be Applied Effectively to Central Cameras?

  IEEE Conference on Computer Vision and Pattern Recognition, IEEE, pp. 1391- 1398, 2013.

- FILIPPO BERGAMASCO, LUCA COSMO, ANDREA ALBARELLI , ANDREA TORSELLO

  A Robust Multi-Camera 3D Ellipse Fitting for Contactless Measurements

  2nd Joint 3DIM/3DPVT Conference 3D Imaging, Modeling, Processing, Visualization, Transmission, IEEE, pp. 168- 175., 2012.

- FILIPPO BERGAMASCO, ANDREA ALBARELLI, ANDREA TORSELLO

  Pi-Tag: a fast image-space marker design based on projective invariants

  MACHINE VISION AND APPLICATIONS (ISSN:0932-8092), pp. 1295- 1310, 2013.

Published Papers

- ANDREA ALBARELLI, FILIPPO BERGAMASCO, AUGUSTO CELENTANO, LUCA COSMO, ANDREA TORSELLO

  Using multiple sensors for reliable markerless identification through supervised learning

  MACHINE VISION AND APPLICATIONS (ISSN:0932-8092), pp. 1539- 1554, 2013.

- FILIPPO BERGAMASCO, ANDREA ALBARELLI, ANDREA TORSELLO

  A Practical Setup for Projection-based Augmented Maps

  First International Conference on Software and Emerging Technologies for Education, Culture, Entertaiment, and Commerce: New Directions in Multimedia Mobile Computing, Social Networks, Human-Computer Interaction and Communicability, Blue Herons, pp. 13- 22., 2012.

Published Papers

Università Ca' Foscari Venezia

- Unconstrained Imaging Model
  - Calibration
  - Rays interpolation
  - Central + Model-free distortion
- Flow and Dichromatic model recovery
  - Problem formulation
  - TV regularizer
  - > Results

F. Bergamasco, A. Albarelli, A. Torsello, M. Favaro, P. Zanuttigh

Pairwise Similarities for Scene Segmentation combining Color and Depth data

21st International Conference on Pattern Recognition (ICPR 2012), IEEE COMPUTER SOCIETY, pp. 3565- 3568 , 2012.

Luca Cosmo, Andrea Albarelli, Filippo Bergamasco

A low cost tracking system for position-dependent 3D visual interaction

Proceedings of the 2014 International Working Conference on Advanced Visual Interfaces - AVI '14, ACM Association for Computing Machinery, pp. 351- 352, 2014.

A. Albarelli, F. Bergamasco, L. Rossi, S. Vascon, A. Torsello

A Stable Graph-Based Representation for Object Recognition through High-Order Matching

21st International Conference on Pattern Recognition (ICPR 2012), IEEE COMPUTER SOCIETY, pp. 3341- 3344, 2012.

Published Papers

- EMANUELE RODOLÃĂ, ANDREA ALBARELLI, FILIPPO BERGAMASCO, ANDREA TORSELLO

  A Scale Independent Selection Process for 3D Object Recognition in Cluttered Scenes

  INTERNATIONAL JOURNAL OF COMPUTER VISION (ISSN:0920-5691), pp. 129- 145 , 2013.

- ANDREA ALBARELLI, FILIPPO BERGAMASCO, ANDREA TORSELLO

  Rigid and Non-rigid Shape Matching for Mechanical Components Retrieval

  11th IFIP TC 8 International Conference, CISIM 2012, Springer, pp. 168- 179 , 2012.

- FILIPPO BERGAMASCO, ANDREA ALBARELLI, ANDREA TORSELLO

  A graph-based technique for semi-supervised segmentation of 3D surfaces

  PATTERN RECOGNITION LETTERS (ISSN:0167-8655), pp. 2057- 2064 , 2012.

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Published Papers

- E. Rodola, Alex M. Bronstein, A. Albarelli, F. Bergamasco, A. Torsello

  A Game-Theoretic Approach to Deformable Shape Matching

  IEEE Computer Society Conference on Computer Vision and Pattern Recognition (CVPR 2012), 2012.

- F. Leckler, F. Ardhuin, A. Benetazzo, F. Fedele, F. Bergamasco, V. Dulov

  Space-time properties of wind-waves: a new look at directional wave distributions

  EGU General Assembly 2014, At Vienna, Austria, Volume: Vol. 16, EGU2014-13508-2, 2014.

- A. Benetazzo, F. Bergamasco, F. Barbariol, A. Torsello, S. Carniel, M. Sclavo

  Towards an Operational Stereo System for Directional Wave Measurements from Moving Platforms

  SME 2014 33rd International Conference on Ocean, Offshore and Arctic Engineering (OMAE2014), 2014.