Outlier Detection for Multi-Sensor Super-Resolution in Hybrid 3-D Endoscopy

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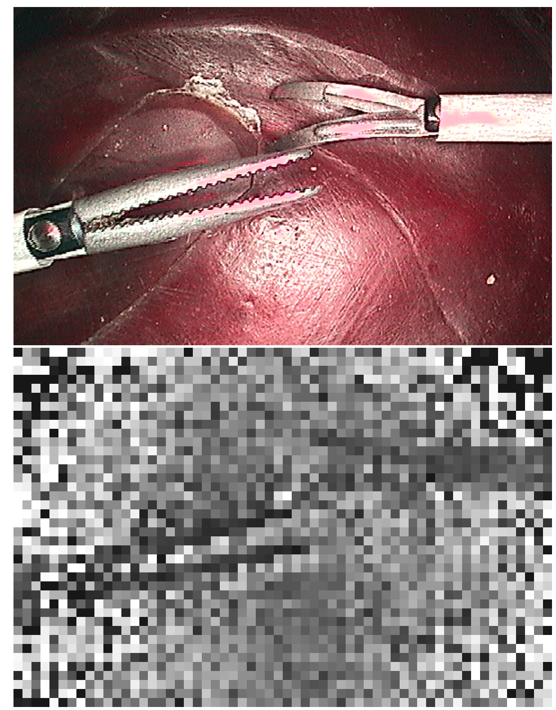
Introduction

Hybrid 3-D Endoscopy

- **Sensor fusion** of photometric (RGB) and 3-D range data (e. g. Time-of-Flight, structured light) in one endoscope[1]
- Exploit information of **complementary modalities** which is beneficial for
  - Segmentation
  - Registration
- We examine restoration of low-resolution range data by means of super-resolution guided by photometric data
  $\rightarrow$ **Multi-sensor super-resolution**



RGB + Time-of-Flight (ToF) data

[1] Sven Haase, Christoph Forman, Thomas Kilgus, Roland Bammer, Lena Maier-Hein, Joachim Hornegger: ToF/RGB Sensor Fusion for 3-D Endoscopy. Current Medical Imaging Reviews 9 (2), 2013, 113-119

Outline

Multi-Sensor Super-Resolution

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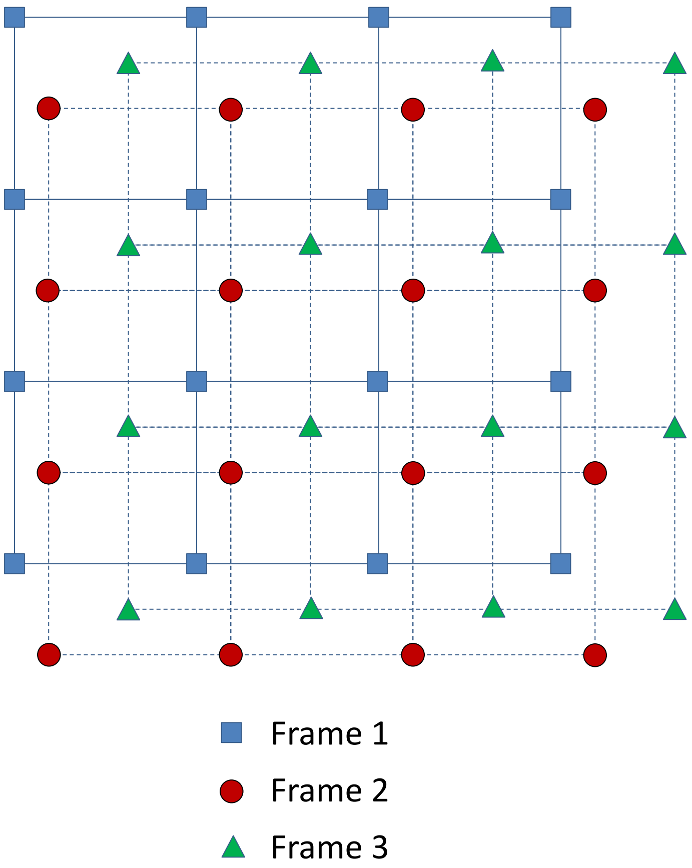
Super-Resolution: Basic Idea

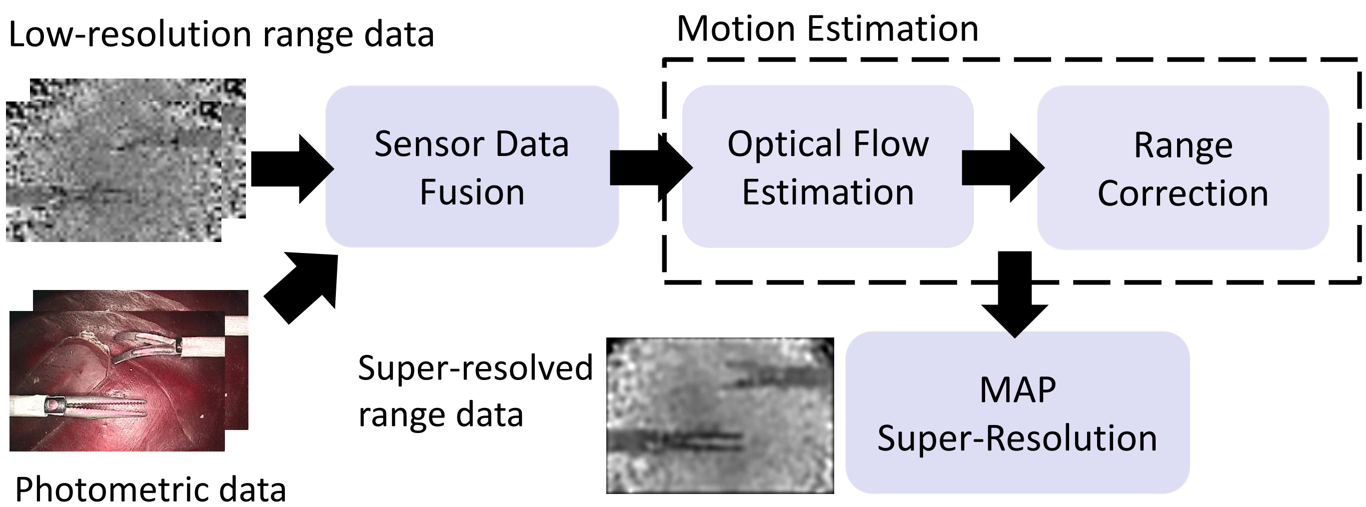
- **Given:** Multiple low-resolution frames (warped with sub-pixel motion)
- If sub-pixel motion is known: Fuse low-resolution frames into new high-resolution image

Sub-pixel motion
$\Rightarrow$ finer sampling



Multi-Sensor Super-Resolution

Flowchart for multi-sensor super-resolution[2]:

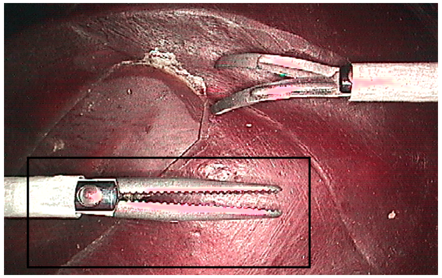


- Robust motion estimation (optical flow) on photometric data
- Maximum a-posteriori (MAP) super-resolution for range data reconstruction

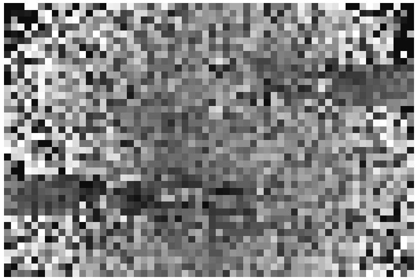
[2]Thomas Köhler, Sven Haase, Sebastian Bauer, Jakob Wasza, Thomas Kilgus, Lena Maier-Hein, Hubertus Feußner, Joachim Hornegger: ToF Meets RGB: Novel Multi-Sensor Super-Resolution for Hybrid 3-D Endoscopy. MICCAI 2013, 139-146

Example

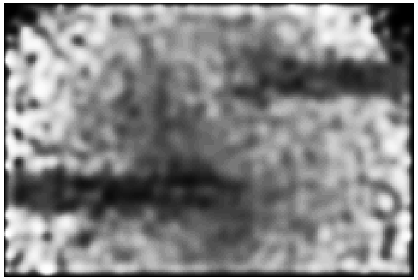
Single-sensor (SSR) vs. multi-sensor super-resolution (MSR):



RGB image

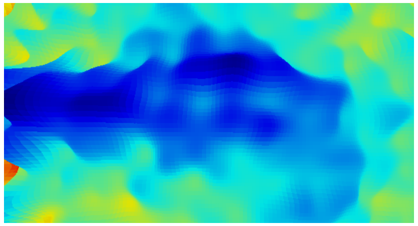


Range image

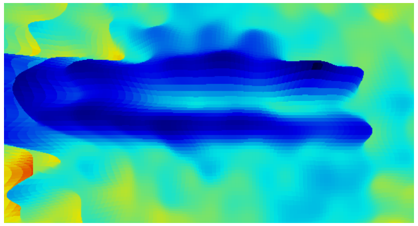


SSR

MSR



SSR (3-D mesh)



MSR (3-D mesh)

Accurate reconstruction thanks to reliable motion estimation on photometric data

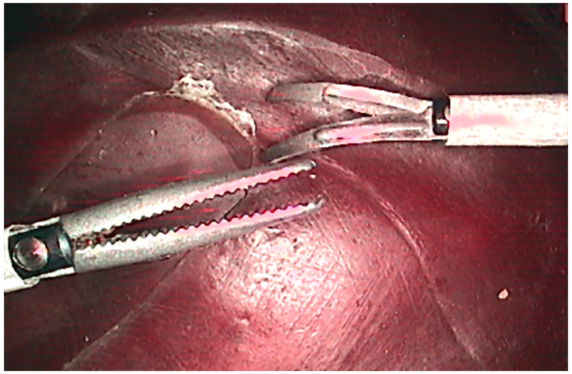
Robustness Issues

Super-resolution reconstruction is sensitive to **outliers**

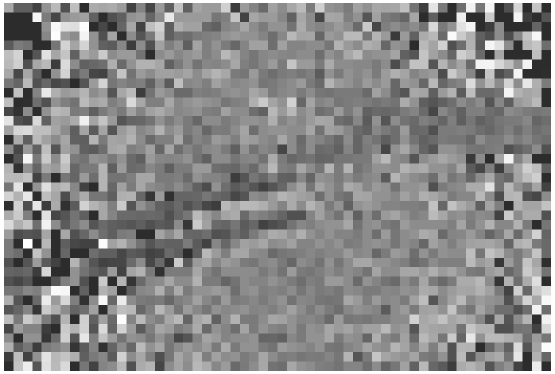
- **Displacement fields:**
  - Occlusions in optical flow estimation
  - Large displacements (of endoscopic tools) and non-rigid deformation
  - Specular highlights
  - . . .
- **Range data outliers:**
  - Flying pixels
  - Specular highlights (invalid range measurements)
  - Distance-dependent noise (no Gaussian noise)
  - . . .

Robustness Issues

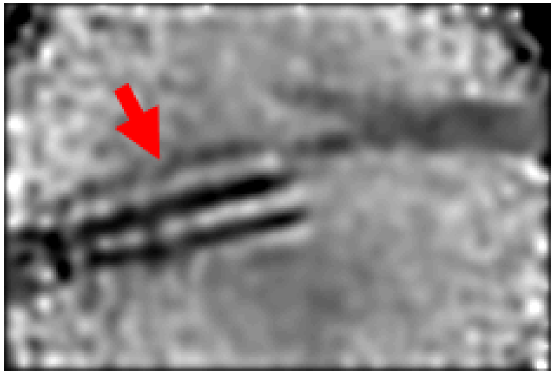
Example for liver phantom data:



RGB image



Range image



Super-resolved (MSR)

Super-resolution sensitive to mis-registrations in optical flow computation

Robust Multi-Sensor Super-Resolution

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Problem Formulation

- We formulate robust multi-sensor super-resolution as:

$$\hat{\mathbf{x}} = \arg\min_{\mathbf{x}} \left\{ \sum_i \beta_i \left| r_i(\mathbf{x}) \right| + \lambda \cdot R(\mathbf{x}) \right\} \tag{1}$$

β_i measures the confidence for the i-th pixel in $\mathbf{r}$

- Residual error to measure data fidelity: $r(\mathbf{x}) = (\mathbf{r}^{(1)}, \ldots, \mathbf{r}^{(K)})^\top$

$$\mathbf{r}^{(k)} = \mathbf{y}^{(k)} - \gamma_m^{(k)} \mathbf{W}^{(k)} \mathbf{x} - \gamma_a^{(k)} \mathbf{1} \tag{2}$$

$\mathbf{x}$: unknown high-resolution range image
$\mathbf{y}^{(k)}$: k-th low-resolution range image
$\mathbf{W}^{(k)}$: system matrix to map $\mathbf{x}$ to $\mathbf{y}^{(k)}$
$\gamma_m^{(k)}$, $\gamma_a^{(k)}$: range correction parameters for k-th frame

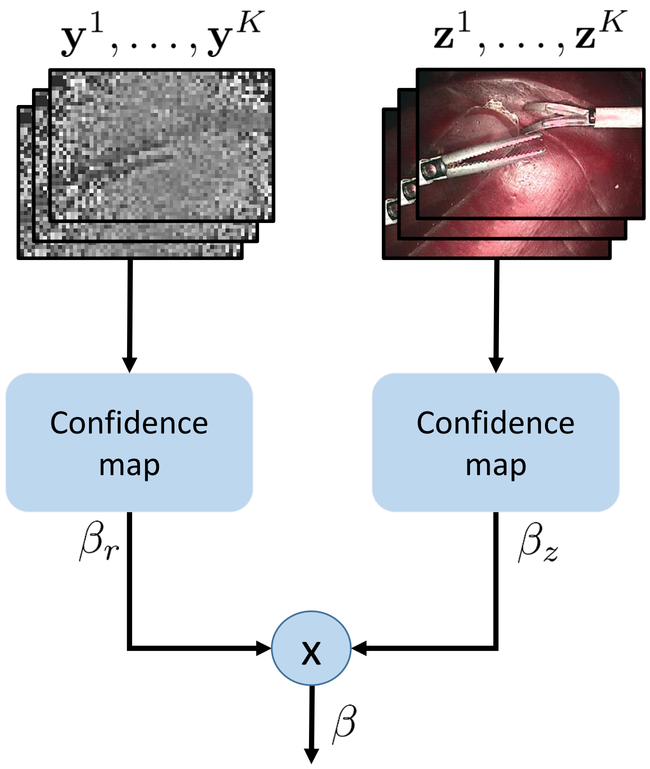
- Huber prior employed for regularizer $R(\mathbf{x})$ to enforce smoothness for $\mathbf{x}$

Outlier Detection Scheme

- Outliers are detected on photometric and range data:
$$\beta_i = \beta_{r,i} \cdot \beta_{z,i} \tag{3}$$
$\rightarrow$ Joint confidence map: β

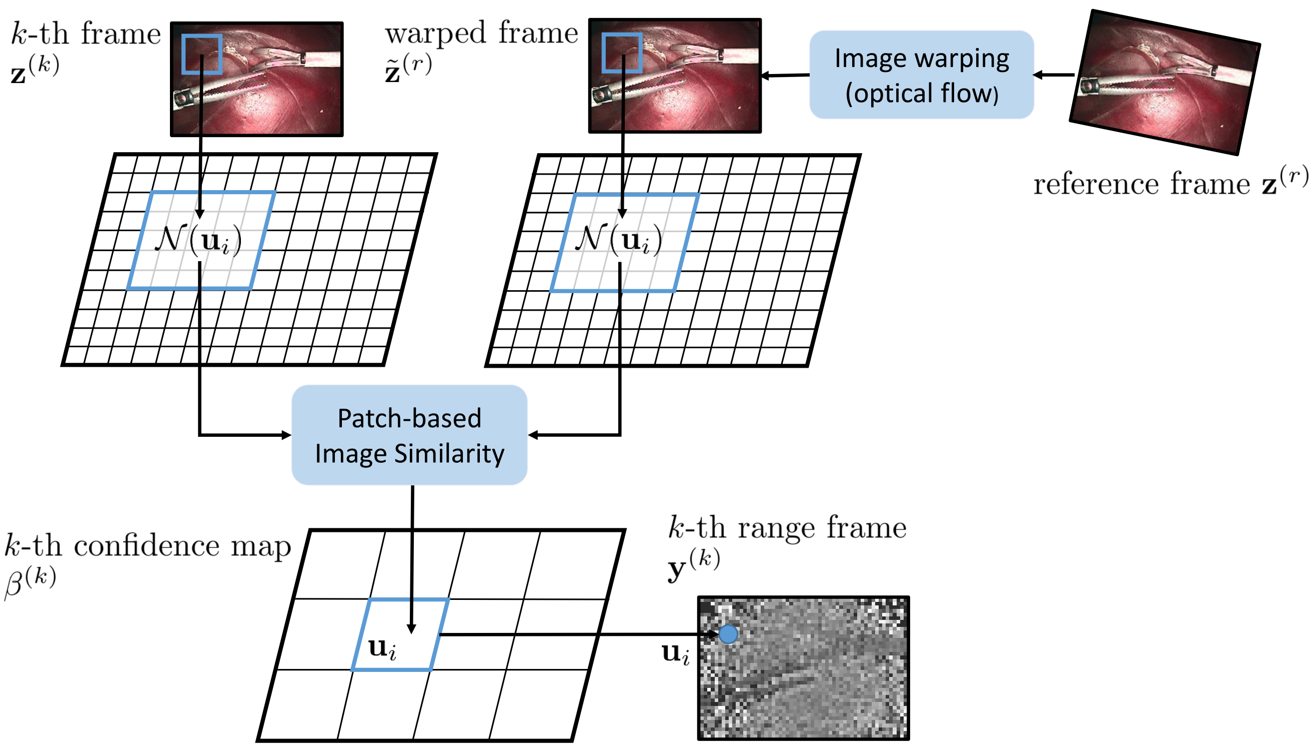
- Displacement estimation outliers are detected on photometric data
$\rightarrow$ Confidence map: β_z

- Range outliers are detected on range data directly
$\rightarrow$ Confidence map: β_r



Displacement Outlier Detection

- Detect outliers by local (patch-wise) image similarity analysis:



Displacement Outlier Detection

- Warp reference frame $\mathbf{z}^{(r)}$ to $\mathbf{z}^{(k)}$ according to estimated optical flow
- Similarity measure for patches $\mathcal{N}(\mathbf{u}_i)$ on photometric data
  $\rightarrow$ Mapped onto range images
  - Patch-wise normalized cross correlation (NCC) $\rho_{z,i}$
  - Thresholding to suppress outliers:

$$\beta_{z,i} = \begin{cases} 0 & \text{if } \rho_{z,i} < \epsilon_z \quad \rightarrow \text{outlier} \\ \rho_{z,i} & \text{otherwise} \end{cases} \tag{4}$$

$\rho_{z,i}$ denotes the NCC for the i-th patch $\mathcal{N}(\mathbf{u}_i)$ (associated with i-th range pixel $\mathbf{u}_i$)
ϵ_z is adjusted to the noise level for photometric data ($\epsilon_z = 0.8$ fixed for our experiments)

Range Outlier Detection

- Assumption: Image noise is a combination of Gaussian noise ($\rightarrow L_2$ norm) and Laplacian noise ($\rightarrow L_1$ norm)
  $\rightarrow$ Formulate super-resolution as weighted least squares problem

- **Outlier detection scheme:**
  - Determine initial estimate $\mathbf{x}^{(0)}$ for the super-resolved image with $\beta_r^{(0)} = \mathbf{1}$ and β_z precomputed for displacement outlier detection:

$$\mathbf{x}^{(0)} = \arg\min_{\mathbf{x}} \left\{ \sum_i \beta_i^{(0)} r_i(\mathbf{x})^2 + \lambda \cdot R(\mathbf{x}) \right\} \tag{5}$$

  - Assess $\mathbf{x}^{(0)}$ with the residual error:

$$\mathbf{r}^{(0)} = \mathbf{y}^{(k)} - \gamma_m^{(k)} \mathbf{W}^{(k)} \mathbf{x}^{(0)} - \gamma_a^{(k)} \mathbf{1} \tag{6}$$

  - Derive range confidence map $\beta_r^{(1)}$ using a **weighting function** $\varphi(\mathbf{r}^{(0)})$

Range Outlier Detection

- Obtain refined solution $\mathbf{x}^{(1)}$ with updated confidence map $\beta_i^{(1)} = \beta_{z,i} \cdot \beta_{r,i}^{(1)}$:

$$\mathbf{x}^{(1)} = \arg\min_{\mathbf{x}} \left\{ \sum_i \beta_i^{(1)} r_i(\mathbf{x})^2 + \lambda \cdot R(\mathbf{x}) \right\} \tag{7}$$

- Update $\beta_r^{(\cdot)}$ and $\mathbf{x}^{(\cdot)}$ in an alternated scheme: Sequence of weighted L_2 norm minimization problems
  $\rightarrow$ **Iteratively re-weighted least squares**[3]

[3] John A. Scales and Adam Gersztenkorn. Robust methods in inverse theory. Inverse Problems 4 (1988), 1071-1091

Iteratively Re-weighted Least Squares for Outlier Detection

Super-resolution using IRLS optimization

Given:

- Range images $\mathbf{y}^{(1)}, \ldots, \mathbf{y}^{(K)}$ with displacement vector fields
- Precomputed displacement confidence map β_z

1. Initialize range confidence map $\beta_{r,i}^{(0)} = 1$ for $i = 1, \ldots, KM$ and $t = 0$
2. Determine super-resolved image $\mathbf{x}^{(t)}$:

$$\mathbf{x}^{(t)} = \arg\min_{\mathbf{x}} \left\{ \sum_i \beta_i^{(t)} r_i(\mathbf{x})^2 + \lambda \cdot R(\mathbf{x}) \right\} \quad \text{with} \quad \beta_i^{(t)} = \beta_{r,i}^{(t)} \cdot \beta_{z,i}$$

3. Update range confidence map:

$$\beta_{r,i}^{(t+1)} = \varphi(r_i^{(t)})$$

4. If not converged set $t \leftarrow t + 1$ and goto step 2

Properties

- **Weighting function:** Soft-thresholding for residual error

$$\varphi(r_i) = \begin{cases} 1 & \text{if } |r_i| \leq \varepsilon \qquad \rightarrow \text{inlier} \\ \frac{\varepsilon}{|r_i|} & \text{if } |r_i| > \varepsilon \end{cases} \tag{8}$$

  ε adaptively adjusted per iteration to the median absolute deviation (MAD):
  - ε adapted to the uncertainty of the residual error
  - No manual parameter tuning required

- Numerical optimization based on a **Scaled Conjugate Gradients** scheme

Experiments and Results

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Experimental Evaluation

- **Experiments:**
  - Quantitative evaluation on synthetic data
  - Qualitative evaluation on liver phantom data
- Comparison of proposed method to state-of-the-art super-resolution methods:
  - Baseline: Multi-sensor super-resolution (MSR) with unweighted L_2 norm data fidelity measure
  - MSR with outlier detection and unweighted L_2 data fidelity measure[4]
  - MSR with unweighted L_1 norm data fidelity measure[5]

ToF/RGB endoscope prototype (manufactured by Richard Wolf GmbH, Knittlingen, Germany)

[4] Wen Yi Zhao and Harpreet Sawhney. Is Super-Resolution with Optical Flow Feasible? ECCV 2002, 599-613
[5] Sina Farsiu, M. Dirk Robinson, Michael Elad, Peyman Milanfar. Fast and Robust Multiframe Super Resolution. IEEE Transactions on Image Processing, 13(10), 1327-1344, 2004

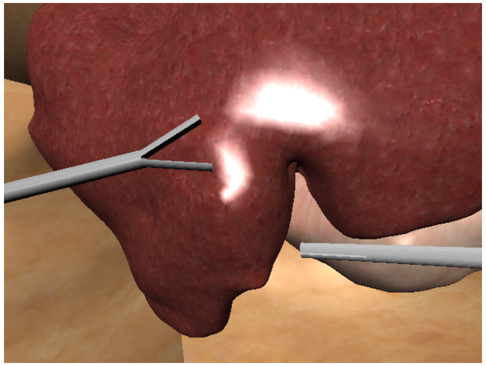
Synthetic Images

Quantitative evaluation: 4 synthetic datasets generated by ToF/RGB simulator

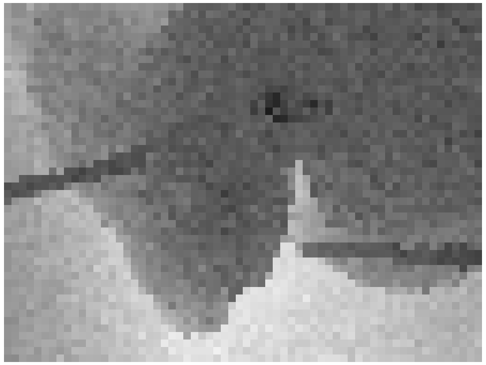
- S1: Small, random endoscope movements (baseline scenario)
- S2: Larger endoscope movements
- S3: Shifting surgical tools
- S4: Movements due to respiratory motion

Simulation: Errors simulated in range data

- Distance-dependent Gaussian noise
- Blur
- Flying pixels
- Specular highlights



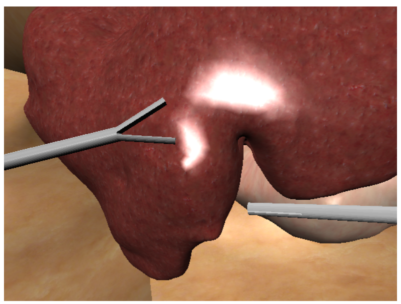
RGB image (640 $\times$ 480)



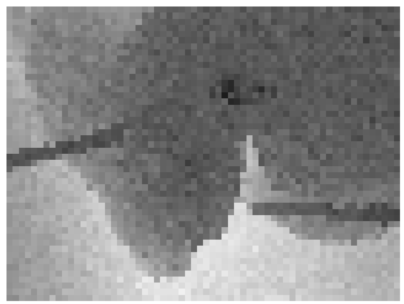
Range image (64 $\times$ 48)

Synthetic Images

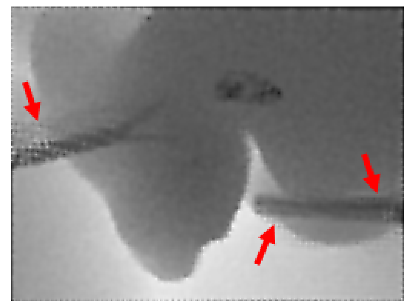
Example: Movements of surgical tools (S3)
Super-resolution results ($K = 31$ frames, magnification factor: 4)



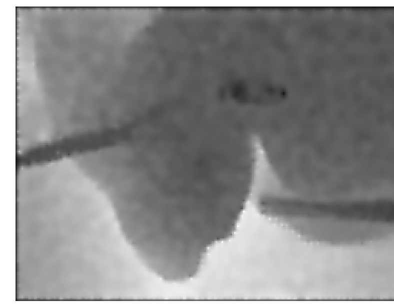
RGB data



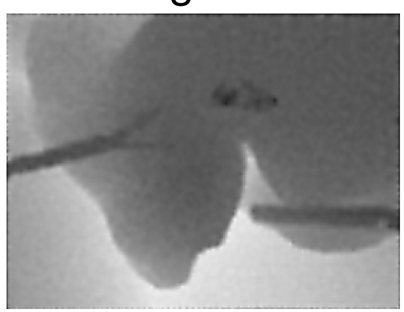
Range data



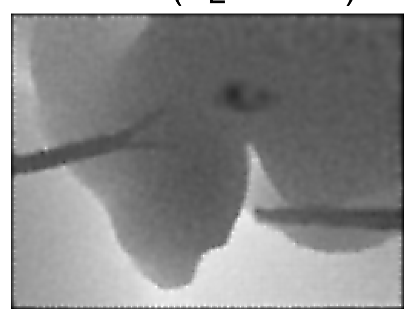
MSR (L_2 norm)



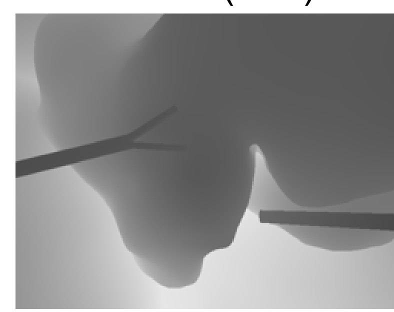
MSR (OD)



MSR (L_1 norm)



Proposed



Ground truth

Synthetic Images

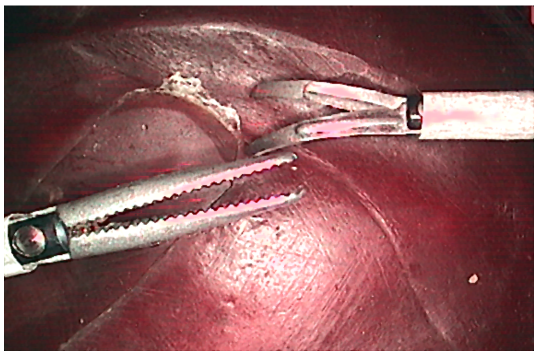
Sliding window processing ($K = 31$ frames, magnification factor: 4) over the datasets using peak-signal-to-noise ratio (PSNR) and the structural similarity (SSIM) index:

Method	**PSNR [dB]**	**SSIM**
L_2 norm	33.11 ± 1.48	0.939 ± 0.008
Outlier detection + L_2 norm	33.06 ± 1.09	0.936 ± 0.005
L_1 norm	34.10 ± 0.68	0.939 ± 0.006
Proposed	$\mathbf{34.54} \pm \mathbf{0.75}$	$\mathbf{0.943} \pm \mathbf{0.003}$

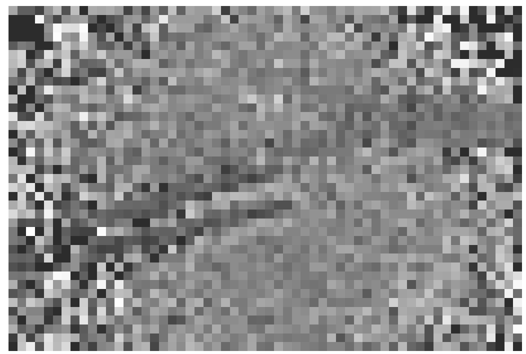
- Improved robustness compared to L_2 norm MSR approach
- Higher accuracy compared to L_1 norm and outlier detection approach (Wilcoxon signed rank test: significant with $P < 0.01$)

Phantom Data

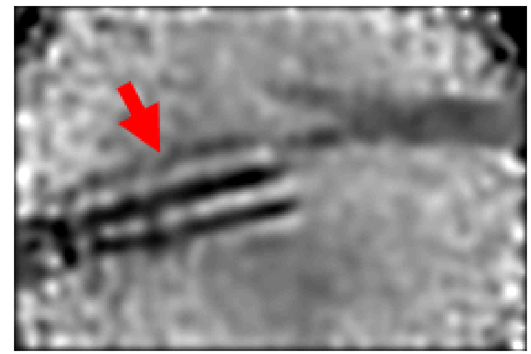
Super-resolution results ($K = 31$ frames, magnification factor: 4)



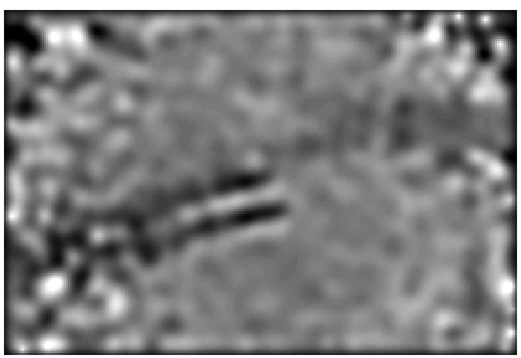
RGB data



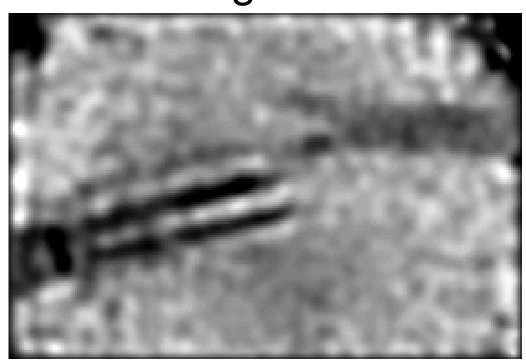
Range data



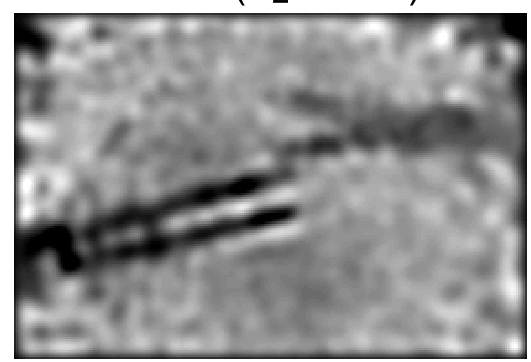
MSR (L_2 norm)



MSR (Outlier detection)



MSR (L_1 norm)



Proposed

Summary and Conclusion

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Summary and Conclusion

- Joint outlier detection scheme for multi-sensor super-resolution: Displacement and range outlier detection
- Enhanced robustness to baseline method without outlier detection
- Improved accuracy compared to other state-of-the-art methods

Future Work:

- Modeling of sensor-specific properties for confidence maps (e. g. specular highlights in ToF)
- Evaluation of different weighting schemes

Supplementary Material

- A super-resolution toolbox (Matlab & MEX/C++) and datasets used for our experiments are available on our webpage:

  http://www5.cs.fau.de/research/data

- **Errata** for typesetting in published workshop proceedings:
  - Modified paper title
  - Shortened abstract with typo
  - Wrongly formatted table and equation
  - Acknowledgments omitted

  We provide the original version of the paper

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