Medical Image Processing for Interventional Applications

Image Enhancement

Online Course – Unit 15

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Topics

Image Enhancement

- Motivation
- Normalized Convolution
- Bilateral Filtering

Summary

- Take Home Messages
- Further Readings

Range Imaging (RI)

Metric surface measurement:

- Marker-less, non-intrusive
- Real-time capable

Specification	PMD CamCube 3.0	Microsoft Kinect
Principle	ToF	SL
Resolution [px]	200 x 200	640 x 480
Frame rate [Hz]	40	30
Measurement range [m]	0.3 – 7.0	1.0 – 3.0
Field of view [°]	40 x 40	57 x 43
Noise level σ [mm] (at a working distance of 1 m)	$\pm$ 5.98	$\pm$ 0.92

Table 1: Comparison of the ToF camera model PMD CamCube 3.0 (top left) to the first generation of Kinect sensors for Xbox 360 (top right)

Figure 1: RI data

RI in Abdominal Surgery: Open Surgery

- Fuse pre-operative 3-D planning data and intra-interventional surface measurements:
  - Augmented reality
  - Navigation

- Challenges:
  - Accuracy in a medical environment
  - Real-time requirements in interventional imaging
  - Usability for surgeons and medical staff

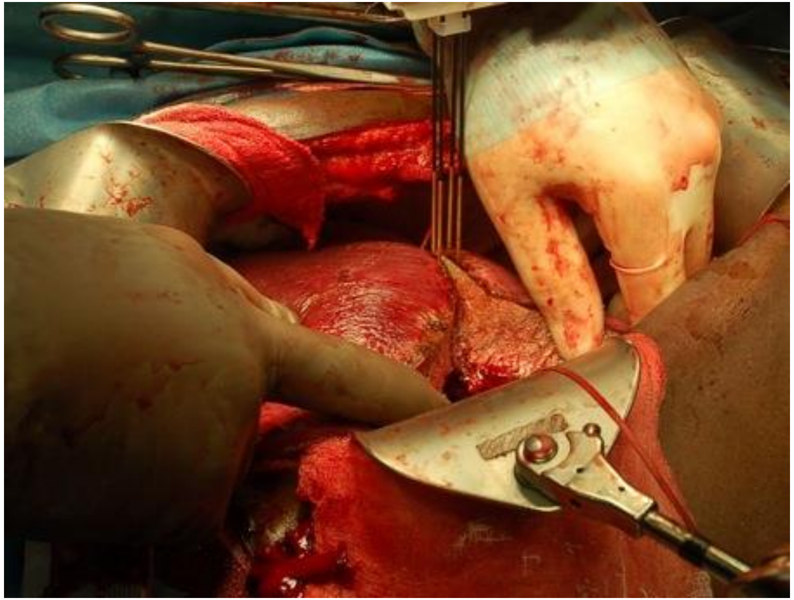


Figure 2: Image courtesy of NJLiverCare.Org

RI in Abdominal Surgery: Endoscopy

- Fuse conventional 2-D RGB endoscopy data with 3-D depth information
  - Measurement of regions of interest
  - Segmentation and tracking of tools
  - Navigation, collision avoidance
- Challenges:
  - Accuracy in a medical environment
  - Real-time requirements in interventional imaging
  - Usability for surgeons and medical staff

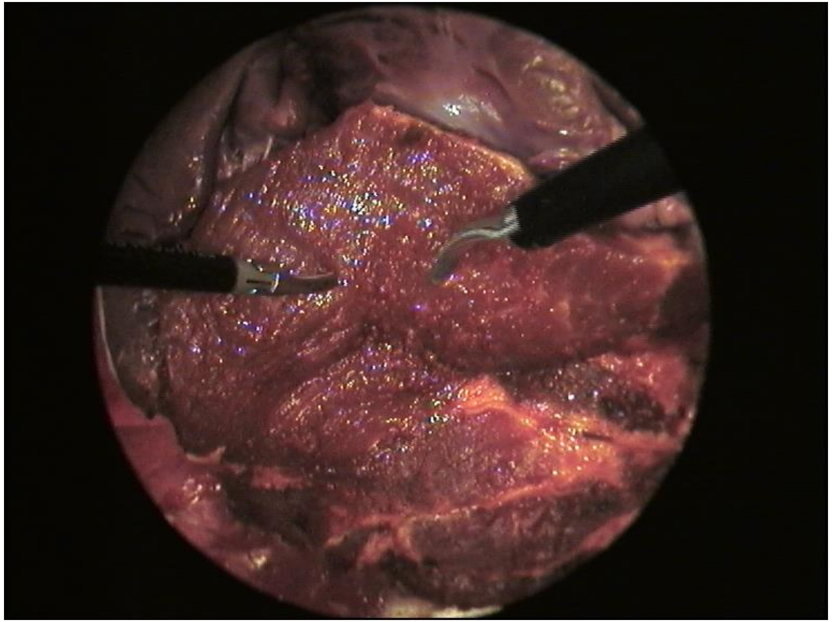


Figure 3: Image courtesy of KIT, Karlsruhe

RI in Abdominal Surgery

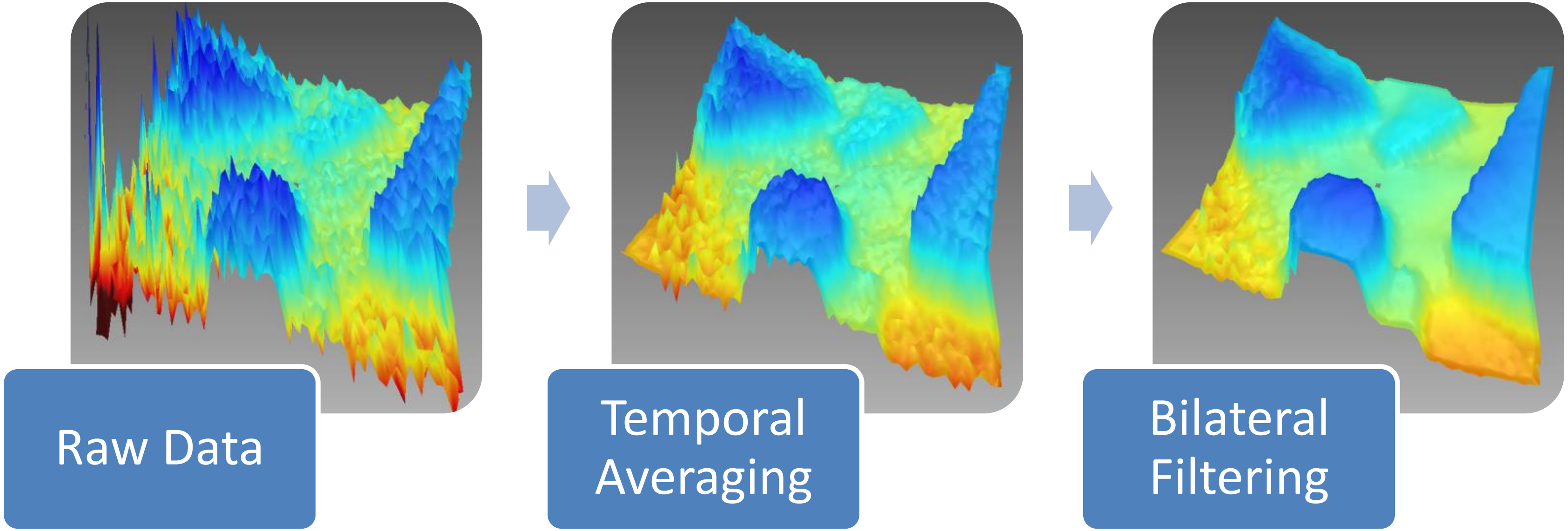
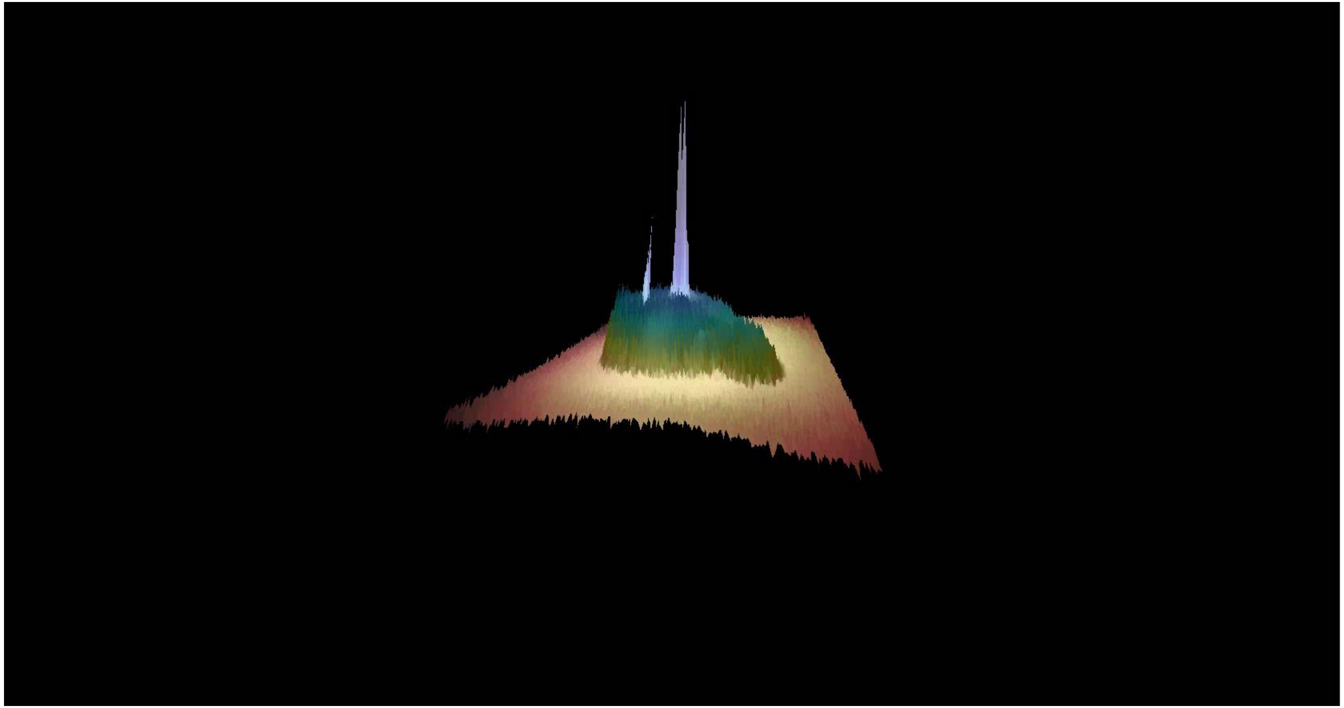


Figure 4: Preprocessing pipeline for interventional range imaging

RI in Abdominal Surgery: Example Video



Video 1: Hover over the static image and click play to watch

Nomenclature

- We consider discrete 2-D images using the following notation:
  - number of pixels N,
  - discrete pixel index $\boldsymbol{x} = (x, y)$,
  - local neighborhood $\omega_{\boldsymbol{x}},\ |\omega_{\boldsymbol{x}}| = (2r + 1)^2,\ r = 1,2, \ldots$.

- Filter input → corrupted/noisy image $g(\boldsymbol{x})$
- Filter output → restored/denoised image $f(\boldsymbol{x})$

Refresher: Convolution

- Discrete convolution:

$$f(\boldsymbol{x}) = \{g * \mathcal{K}\}(\boldsymbol{x}) = \frac{\sum_{\boldsymbol{x}' \in \omega_{\boldsymbol{x}}} g(\boldsymbol{x}')\mathcal{K}(\boldsymbol{x}, \boldsymbol{x}')}{\sum_{\boldsymbol{x}' \in \omega_{\boldsymbol{x}}} \mathcal{K}(\boldsymbol{x}, \boldsymbol{x}')}$$

- Gaussian kernel:

$$\mathcal{K}(\boldsymbol{x}, \boldsymbol{x}') = \exp\left(-\frac{\|\boldsymbol{x} - \boldsymbol{x}'\|_2^2}{\sigma^2}\right)$$

- Convolution theorem for linear, shift-invariant kernels:

$$g * \mathcal{K} = \mathcal{F}^{-1}\{\mathcal{F}\{g * \mathcal{K}\}\} = \mathcal{F}^{-1}\{\mathcal{F}\{g\} \cdot \mathcal{F}\{\mathcal{K}\}\}$$

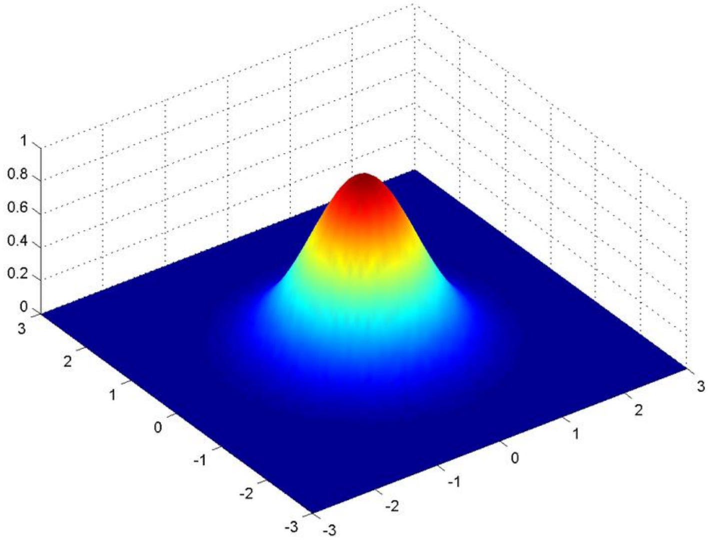


Figure 5: Example of a Gaussian kernel function

Normalized Convolution

- Discrete convolution:

$$f(\boldsymbol{x}) = \frac{\sum_{\boldsymbol{x}' \in \omega_{\boldsymbol{x}}} g(\boldsymbol{x}')\mathcal{K}(\boldsymbol{x}, \boldsymbol{x}')}{\sum_{\boldsymbol{x}' \in \omega_{\boldsymbol{x}}} \mathcal{K}(\boldsymbol{x}, \boldsymbol{x}')}$$

- Normalized convolution (Knutsson and Westin, 1993):

$$f_{\mathrm{NC}}(\boldsymbol{x}) = \frac{\sum_{\boldsymbol{x}' \in \omega_{\boldsymbol{x}}} g(\boldsymbol{x}')\mathcal{A}(\boldsymbol{x}, \boldsymbol{x}')\mathcal{C}(\boldsymbol{x}')}{\sum_{\boldsymbol{x}' \in \omega_{\boldsymbol{x}}} \mathcal{A}(\boldsymbol{x}, \boldsymbol{x}')\mathcal{C}(\boldsymbol{x}')}$$

- Examples for certainty and applicability:

$$\mathcal{C}(\boldsymbol{x}) = \begin{cases} 1, & \text{if } g(\boldsymbol{x}) \text{ is valid} \\ 0, & \text{else} \end{cases}$$

$$\mathcal{A}(\boldsymbol{x}, \boldsymbol{x}') = \mathcal{K}(\boldsymbol{x}, \boldsymbol{x}')$$

Bilateral Filtering

Problem: Conventional filters smooth across edges.

Idea: Incorporate edge-stopping functionality based on pixel similarity.

- Bilateral filter (Tomasi and Manduchi, 1998):

$$f_{\mathrm{BF}}(\boldsymbol{x}) = \frac{\sum_{\boldsymbol{x}' \in \omega_{\boldsymbol{x}}} g(\boldsymbol{x}') c(\boldsymbol{x}, \boldsymbol{x}') s\big(g(\boldsymbol{x}), g(\boldsymbol{x}')\big)}{\sum_{\boldsymbol{x}' \in \omega_{\boldsymbol{x}}} c(\boldsymbol{x}, \boldsymbol{x}')\, s\big(g(\boldsymbol{x}), g(\boldsymbol{x}')\big)}$$

- Spatial closeness c and range similarity s:

$$c(\boldsymbol{x}, \boldsymbol{x}') = \exp\left(-\frac{\|\boldsymbol{x} - \boldsymbol{x}'\|_2^2}{\sigma_c^2}\right)$$

$$s\big(g(\boldsymbol{x}), g(\boldsymbol{x}')\big) = \exp\left(-\frac{|g(\boldsymbol{x}) - g(\boldsymbol{x}')|^2}{\sigma_s^2}\right)$$

Bilateral Filtering

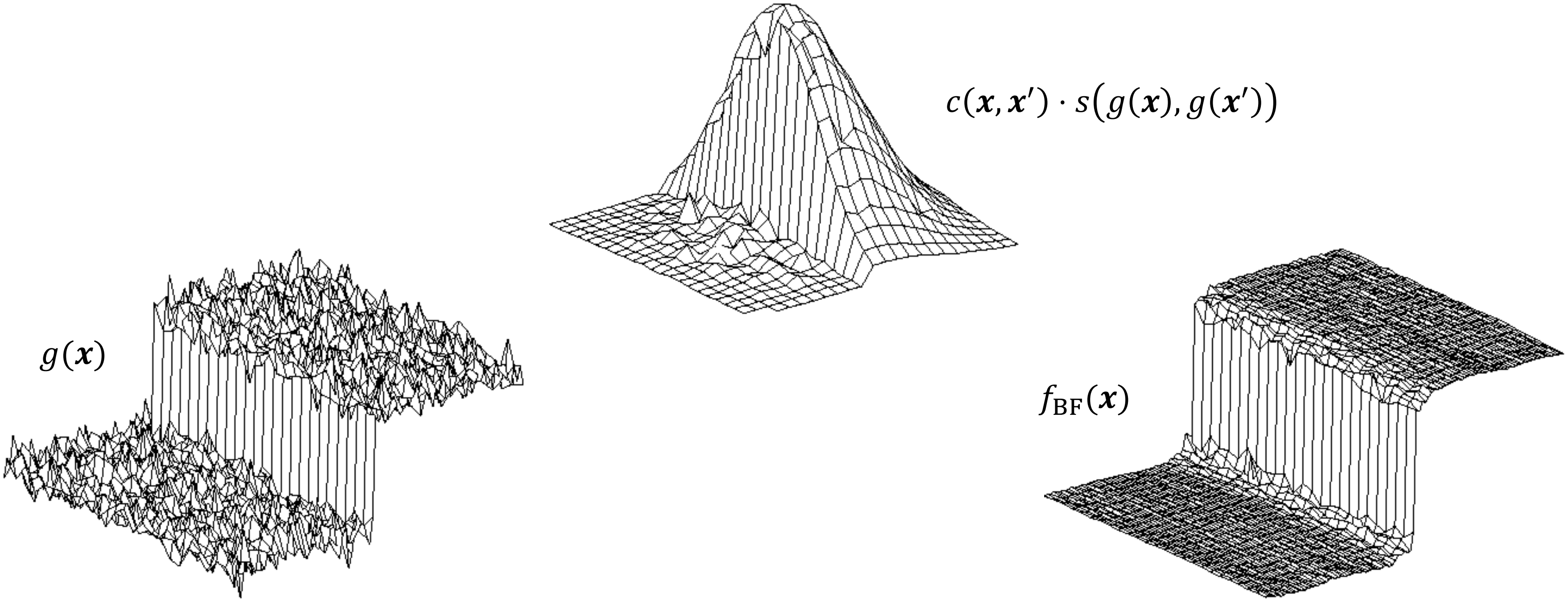


Figure 6: Working principle of the bilateral filter (images from Tomasi and Manduchi, 1998)

Bilateral Filtering

- Properties:
  - Edge-preserving denoising
  - Related to normalized convolution
  - Range similarity term **not** shift-invariant
- Complexity: $\mathcal{O}(Nr^2)$
- Closeness and similarity not restricted to the Gaussian case

Topics

Image Enhancement

Motivation

Normalized Convolution

Bilateral Filtering

Summary

Take Home Messages

Further Readings

Take Home Messages

- By range imaging several imaging applications for surgical treatments are motivated.
- In preparation for the guided filter in the next unit we have learned about normalized convolution and the important bilateral filter.
- The bilateral filter is one example for an edge-preserving filtering method for denoising.

Further Readings

- Hans Knutsson and Carl-Fredrik Westin. “Normalized and Differential Convolution: Methods for Interpolation and Filtering of Incomplete and Uncertain Data”. In: *Proceedings of IEEE Conference on Computer Vision and Pattern Recognition*. IEEE, June 1993, pp. 515–523. DOI: 10.1109/CVPR.1993.341081
- Carlo Tomasi and Roberto Manduchi. “Bilateral Filtering for Gray and Color Images”. In: *Sixth International Conference on Computer Vision, 1998. Sponsored by the IEEE Computer Society, January 4-7, 1998, Bombay, India*. IEEE, Jan. 1998, pp. 839–846. DOI: 10.1109/ICCV.1998.710815