Semiar: Selected Topics in Variational Image Processing

Orientational meeting

WS 2014/2015

Michael Möller,
Thomas Möllenhoff,
Mohamed Souiai,
Daniel Cremers
Computer Vision Group
Department of Computer Science
TU München

Objectives of the seminar

What is happening here?

- We briefly present 15 seminar topics.

Michael Möller, Thomas Möllenhoff, Mohamed Souiai, Daniel Cremers

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- Starting from Oct. 29th the seminar will be every Wednesday at 2pm c.t. with two talks per meeting.

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- Talks are 35min with 10min discussion afterwards.
- The last seminar is the week before Christmas.
- You have to write a 5-7 page report about your topic which is due on Jan. 7th, 2015.

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What you will learn in this seminar

Goals

- Get an impression of recent advances in variational image processing in various applications.
- Learn how to study a recent research paper and get a deep understanding of one particular topic.
- Write a scientific report.
- Practice giving scientific talks.

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Requirements, or “is this something for me?”

Necessary

- Good background and interest in mathematics.
- Working knowledge about basic linear algebra and multivariable calculus in finite dimensions.

Recommended

- Computer Vision fundamentals from any basic course.
- Having heard about variational methods.

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Important Dates

- First meeting: Today (02.07.2014)
- Registration: starting from **04.07**.
- We assign the topics and talks and will write you an email.
- Weekly presentations starting on **Wednesday** Oct. 29th, **14:15-16:00**.
- Read and discuss your assigned topic with your supervisor **early**.
- Deliver and discuss your slides **one week before your presentation**.
- Hand in your report until **Jan. 7th, 2015**.

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Preparation

Please do not work on your topic completely alone!

- Meet your supervisor at least **twice**.
- We recommend: Discuss your topic with your supervisor **one month before your talk**.
- We require: Deliver and discuss your slides **one week before your presentation**.

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Report

- The report should contain an **overview** and the **main contributions** of your assignment.
- Length: **5-7 pages**.
- Language: **English** or **German**.
- Write your report with **Latex** – a template will be available on the course web page.
- Send a **PDF via email** to your supervisor.
- Hand in your report until **Jan. 7th, 2015**.

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Presentation

- **35min talk** with **10min discussion** afterwards.
- Don't put too much information on one slide – 1-2 minutes per slide, i.e. not more than 35 slides!
- Language: **English**.
- You are free to choose the presentation software but need to export to PDF for discussion with your supervisor.

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Evaluation Criteria

You will be evaluated based on the following criteria:

- Gained expertise in the topic.
- Quality of your talk.
- Quality of your report.
- Active participation in the seminar is expected (questions + comments after the talks).

- **Attendance of each seminar is mandatory**!
  In case of absence: medical certificate.

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Lectures on related topics

Variational Methods for Computer Vision

- Structured introduction to variational methods.
- Learn variational modelling for several applications.

Recent advances in computer vision: Numerical Methods for Variational Image Analysis

- After the modeling one typically ends up with $\hat{u} = \arg\min_u E(u)$
- This lecture is about the theory and implementation of numerical optimization methods for actually solving the above problem.

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Overview of available topics

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An Introduction to Total Variation for Image Analysis

- Introduction to image processing and inverse problems.

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An Introduction to Total Variation for Image Analysis

- Introduction to image processing and inverse problems.
- Recover unknown image u from observed image f with noise η.

$$f = Au + \eta$$

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An Introduction to Total Variation for Image Analysis

- Introduction to image processing and inverse problems.
- Recover unknown image u from observed image f with noise η.

$$f = Au + \eta$$

- Highly *ill-posed* problem $\rightarrow$ regularization!
- Formulation as an energy minimization problem:

$$\underset{u}{\operatorname{argmin}} \underbrace{\|Au - f\|^2}_{\textit{Dataterm}} + \underbrace{J(u)}_{\textit{Regularizer}}$$

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An Introduction to Total Variation for Image Analysis

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- Formulation as an energy minimization problem:

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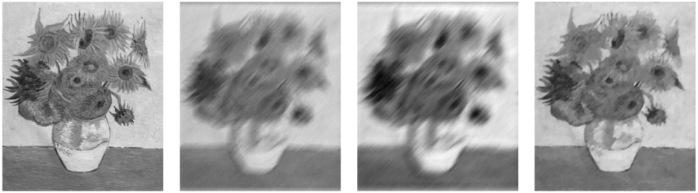
- Total Variation (TV) is one of the most versatile regularizers with many interesting properties.



(a) Original image (b) Degraded image (c) Wiener filter (d) TV-deblurring

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A Convex Formulation of Continuous Multi-Label Problems

- Many optimization problems in computer vision are *nonconvex* and even NP-hard.
- Direct / naive minimization usually leads to poor local optima.

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A Convex Formulation of Continuous Multi-Label Problems

- Many optimization problems in computer vision are *nonconvex* and even NP-hard.
- Direct / naive minimization usually leads to poor local optima.
- Replace initial nonconvex problem by a equivalent higher dimensional convex problem:

$$\underset{u:\Omega\to\Gamma}{\operatorname{argmin}}\ E(u) \quad \Rightarrow \quad \underset{u:\Omega\times\Gamma\to[0,1]}{\operatorname{argmin}}\ \widehat{E}(u)$$

- Possible application: Stereo matching.

$\longrightarrow$

An Approach to Vectorial Total Variation based on Geometric Measure Theory

- Most real world images have multiple channels.

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An Approach to Vectorial Total Variation based on Geometric Measure Theory

- Most real world images have multiple channels.
- How to properly generalize TV from scalar (grayscale) images to vectorial (color) images?

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- Most real world images have multiple channels.
- How to properly generalize TV from scalar (grayscale) images to vectorial (color) images?
- This paper considers a generalization which emerges naturally from geometric measure theory.

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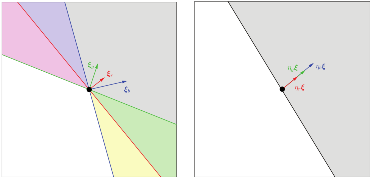
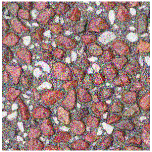
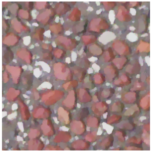


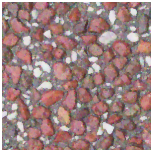
- Here color channels share a common edge direction.



Noisy Input



Naive



Proposed

Spectral Total Variation Decomposition

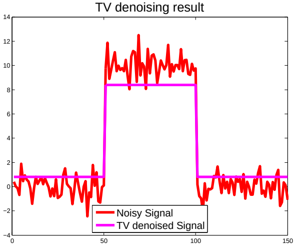
$$\partial_t u(t) = -\,p(t) \;\; \text{s.t. } p(t) \in \partial \left\| \sqrt{(\partial_x u(t))^2 + (\partial_y u(t))^2} \right\|_1$$

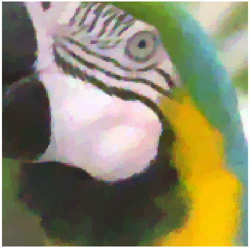
Generalizing what the Fourier transform is for frequencies.

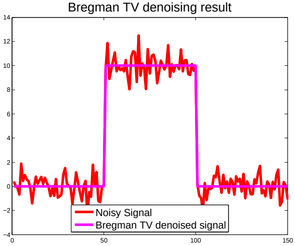
Bregman Iterations

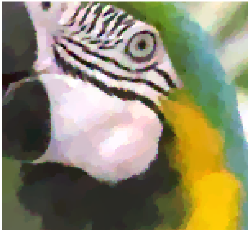
$$\min_u \|Au - f\|^2 + J(u)$$

Correcting the loss of contrast of variational approaches.









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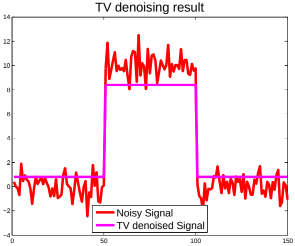
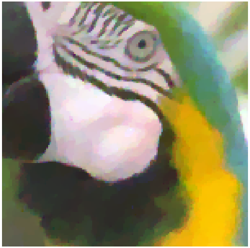
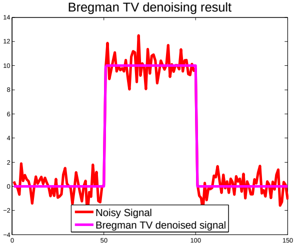
Bregman Iterations

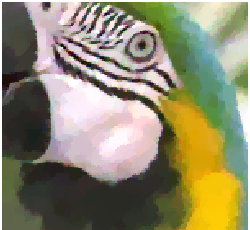
$$\min_u \|Au - f\|^2 + J(u) - \langle p^k, u \rangle \quad \text{s.t. } p^k \in \partial J(u^k)$$

Correcting the loss of contrast of variational approaches.









Exemplar-Based Image Inpainting

- The challenge is to remove large objects from digital images and fill in the hole in visually plausible way.
- Idea: Instead to propagating neighbouring pixel information use a non-local variational scheme and fill in using similar image patches.

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Linear Diffusion based Image Compression with iPiano

- Image compression reduces in some sense the "redundant" data in an image.

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Linear Diffusion based Image Compression with iPiano

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- Image inpainting can be used to restore "missing" data.

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Linear Diffusion based Image Compression with iPiano

- Image compression reduces in some sense the "redundant" data in an image.
- Image inpainting can be used to restore "missing" data.
- Idea: remove pixels which are seen as redundant by the image inpainting algorithm.


Input


Compressed


Restored

- Formulation as an *energy minimization* problem.
- Emphasis on the employed *optimization* method (iPiano).

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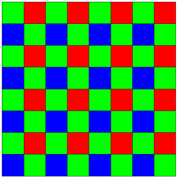
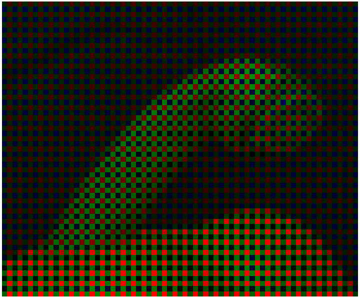
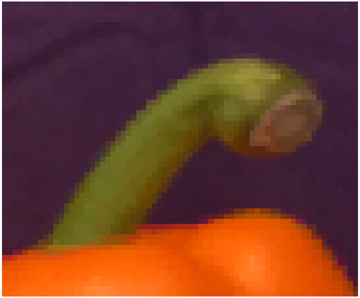
Image Demosaicking

- Cameras only record one color per pixel.
- Sensors have a certain pattern of colors.
- Interpolating missing colors: *Demosaicking*
- $\min_u \|P_I u - f\|^2 + J(u)$







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Dithering by Differences of Convex Functions

- Dithering aims to create the illusion of a *continuous* image given only a limited set of colors.
- Applications in printing and non-photorealistic / artistic rendering.

Input (8 bit)

Dithered (1 bit)

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Input (8 bit)

Dithered (1 bit)

- Physically motivated model based on electrostatic principles.
- Energy minimization problem, emphasis on employed optimization method (“DC Programming”).

Variational Optical Flow

- Given two consecutive images, one looks for a motion field which maps corresponding pixels to one another.
- The overall problem can be formulated in a variational framework via an optimization problem:

$$\min_{v} \int_{\Omega} |I_0(x) - I_1(x + v(x))|^2 + J(v)$$

Variational Super Resolution

- Given a set of low resolution images, construct a high resolution image.
- Exploit redundancy of the input frames and solve an optimization problem of the form:

$$\min_u \sum_i \|DBW_i u - f_i\|_2^2 + J(u)$$

16 input images | Super-resolution $\xi = 3$

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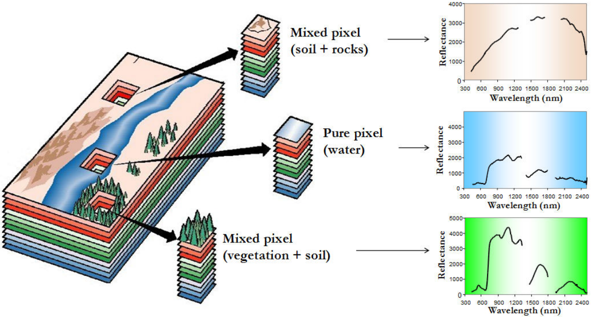
Hyperspectral Unmixing



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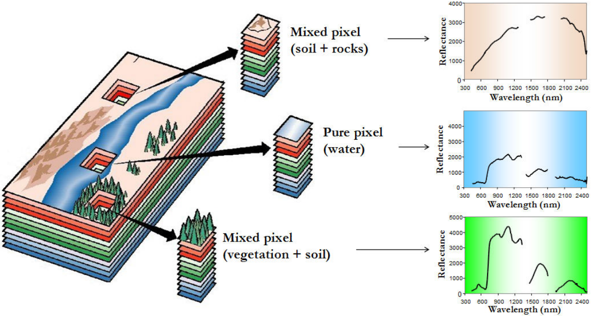

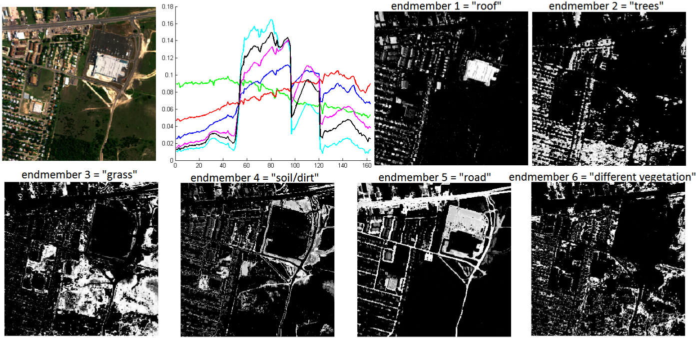

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Pan-Sharpening

Image fusion with local and nonlocal priors:

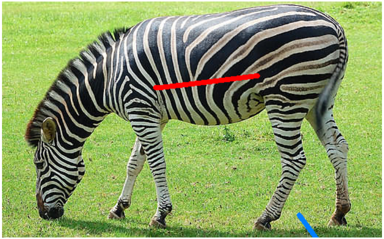
$$\min_u \frac{1}{2}\left\|\sum_i \alpha_i u_i - f\right\|^2 + \frac{\mu}{2}\sum_i \|(\downarrow k) * u_i - g_i\|^2 + J(u)$$

High res. gray scale *f* + low res. color *g* = high res. color *u*

Globally Optimal Two Phase Segmentation

- We wish to dissect an input image in two spatially consistent segments.
- Encode the segmentation as a binary valued function $u(x) \in \{0, 1\}$ and solve the following optimization problem:

$$\min_u J(u) + \int_\Omega u(x)\rho(x) \;\; dx$$



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Multilabel Segmentation

- We wish to find multiple consistent regions of an input image based on user input, color or texture.
- Formulate this combinatorial problem as a variational problem in the following way:

$$\min_u \sum_i^n \int_\Omega u_i(x)\rho_i(x) \; dx + J(u)$$

Singular Vectors of Variational Regularizations

Disclaimer: This is a very theoretical topic!

Well known: singular value decomposition of matrices.

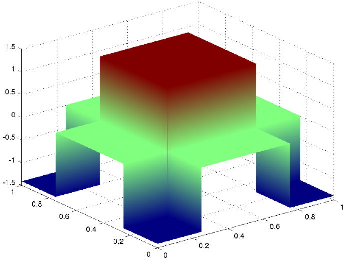
$$K^T K u = \alpha u$$

define $\lambda = 1/\alpha$, $J(u) = \frac{1}{2}\|u\|^2$. Generalization

$$\lambda K^T K u \in \partial J(u)$$

What happens for other J, e.g. $J(u) = TV(u)$?

- Is there an orthonormal basis of singular vectors?
- What properties do singular vectors have?



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End

Any questions?

These slides will be available online at
https://vision.in.tum.de/teaching/ws2014/vms2014
Password: *imageprocessing*