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# Variational Methods for Computer Vision: Exercise Sheet 7

Exercise: December 11, 2014

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## Part I: Theory

The following exercises should be **solved at home**. You do not have to hand in your solutions, however, writing it down will help you present your answer during the tutorials.

1. Let  $Q := [0, 1] \times [0, 1]$  be a rectangular area and let  $v : Q \rightarrow \mathbb{R}^2$  be a differentiable vector field defined on  $Q$  with  $v(x, y) = (a(x, y), b(x, y)) \in \mathbb{R}^2$ .

- (a) Prove Green's theorem:

$$\int_Q b_x(x, y) - a_y(x, y) \, dx \, dy = \oint_{\partial Q} (a \, dx + b \, dy)$$

Assume the boundary curve  $\partial Q$  to be oriented counterclockwise.

Hint: Use the fundamental theorem of calculus.

- (b) Let  $\Omega \subset \mathbb{R}^2$  be an area that can be represented as a disjoint union of a finite number of squares  $Q_1, \dots, Q_n$ . Why does Green's theorem also hold for this set  $Q$ ?
2. Let  $\Omega = [-5; 5] \times [-5; 5]$  be a rectangular area and let  $I : \Omega \rightarrow [0; 1]$  be an image given by:

$$I(x, y) = \begin{cases} 1 & \text{if } x^2 + y^2 \leq 1, \\ 0 & \text{else.} \end{cases}$$

Furthermore let  $C : [0, 1] \rightarrow \Omega$  be a curve represented by a circle centered at the origin having radius  $r$  and local curvature  $\kappa_C$ .

- (a) Write down the two-region piecewise constant Mumford-Shah functional with length regularity weighted by  $\nu$ .
- (b) Write down the corresponding gradient descent for the two cases  $r > 1$  and  $r \leq 1$ .
- (c) Show that the Gâteaux-Derivative at  $r = 1$  is not continuous.
- (d) In which range should  $\nu$  be in order to obtain good segmentation results?

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## Part II: Practical Exercises

This exercise is to be solved **during the tutorial**.

### Super-Resolution from Video.

In the lecture we encountered the concept of super resolution from video. The key idea of super resolution is to exploit redundancy available in multiple frames of a video. Assuming that each input frame is a blurred and downsampled version of a higher resolved image  $u$ , the high-resolution image can be recovered as the minimum of the following energy functional:

$$E(u) = \sum_{i=1}^n \int_{\Omega} ((ABS_i u)(x) - (Uf_i)(x))^2 dx + \lambda \int_{\Omega} |\nabla u(x)| dx. \quad (1)$$

The Linear Operator  $B$  denotes a Gaussian Blurring. The upsampling operator  $U$  simply replaces every pixel with four pixels of the same intensity. In order to be able to compare image  $u$  with the upsampled version of  $f_i$  which is constant blockwise, we apply the linear averaging operator  $A$  on  $u$  which assigns every block of pixels the mean values of the pixels in that block. The linear operator  $S_i$  accounts for the coordinate shift by motion  $s_i$  hence:

$$(S_i u)(x) = u(x + s_i(x)).$$

1. In the following we are going to construct a toy example for super resolution by executing the following steps:

- (a) Download the archive `vmcv_ex07.zip` and unzip it on your home folder. In there should be a file named `Boat.png`.
- (b) Create from the unzipped image 6 versions shifted in  $x$  direction by exactly one pixel hence:

$$f_i(x, y) = f(x + i, y),$$

for  $i = 1 \dots 6$ . In order to account for the boundary, consider taking cropped images from the interior of the original image.

- (c) In order to simulate blurring convolve the shifted images with a gaussian kernel. Next downsample the images  $f_i$  by factor 2 by using the `imresize` function in Matlab with nearest neighbor interpolation.
2. In what follows we are going to minimize the above functional in order to obtain a super resolved image from our input images  $f_i$ .
    - (a) Derive the Euler-Lagrange equation of  $E$  and the corresponding gradient descent scheme.
    - (b) Compute the matrix representations of the linear operators  $A$ ,  $B$ ,  $S_i$  and  $U$ . Since these matrices are huge, again use sparse data structures in Matlab (`spdiags` `speye`) in order to obtain a sparse representation.
    - (c) Compute  $u^* = \operatorname{argmin}_u E(u)$  by means of gradient descent using matrix vector representation after stacking the function  $u$  in a vector using the matlab command `reshape`.