

# Variational Methods for Computer Vision: Exercise Sheet 6

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Exercise: December 5, 2017

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## Part I: Theory

1. Let  $L : X \rightarrow Y$  be a linear operator and  $X, Y$  be finite dimensional vector spaces with  $\dim X = n$  and  $\dim Y = m$ . Let  $\{e_1, \dots, e_n\}$  and  $\{\tilde{e}_1, \dots, \tilde{e}_m\}$  be the bases for  $X$  and respectively for  $Y$ . Show that the operator  $L$  can be represented by an  $m \times n$  matrix  $M$ , hence:

$$L(u) = Mu, \quad \forall u \in X.$$

2. Calculate the Euler-Lagrange equation of the following energy functional

$$E(u) = \int_{\Omega} \mathcal{L}(u(x), \nabla u(x), Au(x)) \, dx,$$

where  $\Omega \subset \mathbb{R}^2$ ,  $u : \Omega \rightarrow \mathbb{R}$ , and  $A : (\Omega \rightarrow \mathbb{R}) \rightarrow (\Omega \rightarrow \mathbb{R})$  is a linear mapping.

Hint: use the adjoint  $A^*$  of the operator  $A$  for which the following identity holds

$$\int_{\Omega} u(x)(Av)(x) \, dx = \int_{\Omega} (A^*u)(x)v(x) \, dx.$$

## 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_ex06.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  $u^* = \arg \min_u E(u)$  by means of gradient descent using matrix vector representation after stacking the function  $u$  in a vector using the matlab command `reshape`.