Final Project
Image Inpainting and Completion

Team 12

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M2: Optimisation and Inference for Computer Vision
Masters in Computer Vision

Universitat Autònoma de Barcelona

Summary

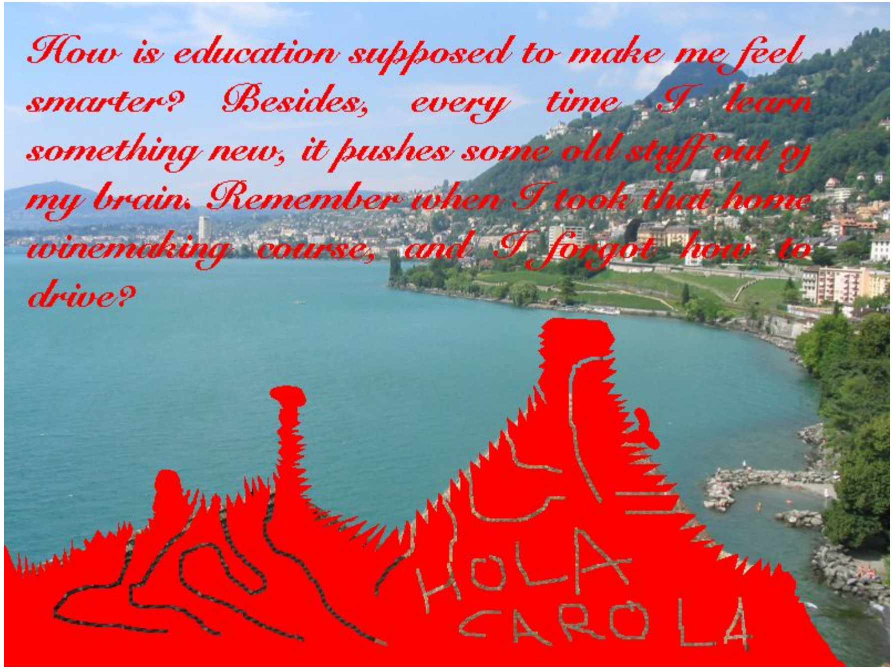
Project Overview

Workflow

- Part I: Image inpainting
- Part II: Image segmentation
- Part III: Natural Image completion

Results and Conclusions

Project Overview



Inpainting
↓
Segmentation
↓
Image completion

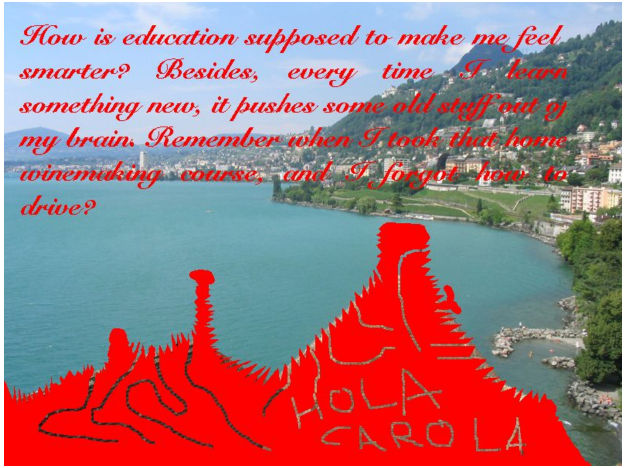
Workflow

Part I: Image inpainting

The aim is to recover information in regions where the original information is missing.

Given an energy functional:

$$\begin{cases} \underset{u \in W^{1,2}(\Omega)}{\arg\min} \int_D |\nabla u(x)|^2 dx, \\ u|_{\partial D} = f \end{cases}$$



Inpainting

↓

Segmentation

↓

Image completion

Being ***f*** the destination function outside the domain *D*, ***u*** an unknown function in the inpainting domain *D* and also a solution of Euler-Lagrange (partial) differential equation.

$$\begin{cases} \Delta u & = & 0 & \text{in } D, \\ u & = & f & \text{in } \partial D \end{cases}$$

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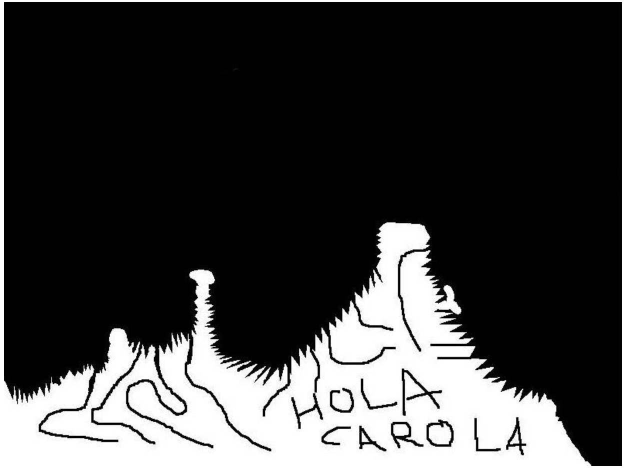
Workflow

Part II: Image segmentation

The goal is to segment the mask of the previous inpainted image according to level sets theory. Chan-Vese algorithm is used to detect contours and create an improved final binary mask.



Inpainting

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Segmentation

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Image completion

The algorithm minimizes the following energy functional:

$$J(\varphi, c_1, c_2) = \mu \int_\Omega \delta(\varphi) \left|\nabla\varphi\right| dxdy + \nu \int_\Omega H(\varphi) dxdy + \ldots$$

$$\ldots + \lambda_1 \int_\Omega H(\varphi)(u - c_1)^2 dxdy + \lambda_2 \int_\Omega \left[1 - H(\varphi)\right](u - c_2)^2 dxdy$$

Where ***φ*** is the level set function, **c1** and **c2** are constants representing the classes and ***μ, ν,*** **λ** are the length, area and fidelity cost terms, respectively.

Workflow

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Workflow

Part III: Natural Image Completion

The final step of the project is to create a nature image completion.

To do so:
· Find from a set of images the most similar ones by using GIST descriptors.
· Find from the selected images the most similar regions.
· Automatically mask fine tuning:

Inpainting
↓
Segmentation
↓
Image completion

- · Define the probability of each pixel to belong to the selected image or the original image.
- · Use graphical models to improve the mask by minimizing the following cost function:

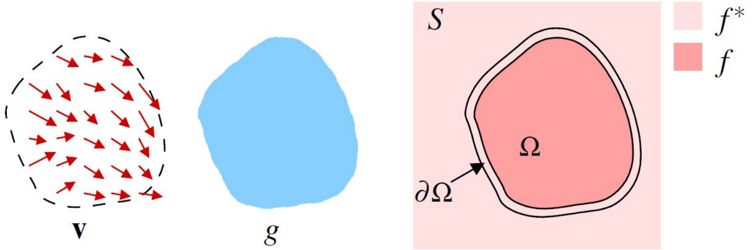
$$C(L) = \sum_{p} C_d(p, L(p)) + \sum_{p,q} C_i(p, q, L(p), L(q))$$

Being ***p*** and ***q*** pixels and ***L(x)*** the assigned label to pixel ***x***.
Where $\boldsymbol{C_d}$ and $\boldsymbol{C_i}$ are the unary and binary potentials, respectively.

Workflow

Part III: Natural Image Completion. Poisson editing

· Clone the similar regions from the selected image to the original one in a seamless way



Given an energy functional:

$$\min_f \iint_\Omega |\nabla f - \mathbf{v}|^2 \text{ with } f|_{\partial\Omega} = f^*|_{\partial\Omega},$$

Inpainting

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Being ***f*** an unknown function in the inpaiting domain Ω, ***f**** the destination function outside the domain Ω and ***v*** a gradient field taken directly from a source image, ***g***.
An unique solution can therefore be found by solving Poisson equation with Dirichlet boundary conditions in Ω:

$$\Delta f = \Delta g \text{ over } \Omega, \text{ with } f|_{\partial\Omega} = f^*|_{\partial\Omega}.$$

Results
Natural Image Completion. Visual inspection

Bad results

Good results

Results
Natural Image Completion. Visual inspection

Bad results

Good results

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Conclusions

- Inpainting is a powerful technique to replace lost or corrupted parts of the image data. Inpainting algorithms use surrounded information to recover small regions or to remove small defects, when this information is not enough, inpainting will not work as it is expected. The possible lack of information is its principal disadvantage.

- Segmentation by using Chan-vese algorithm works in a really intuitive way. Once the energy functional is understood, it is easy to play with the parameters and figure out the important role that they play. One drawback is that the segmentation is based on intensities values difference, that is why, two different well defined textures with the same mean intensity value will not be well segmented.

- Poisson editing allows the seamless importation from source image regions to a destination region given unbelievable results, just by copying somehow the gradient information instead of the pixel information of the image. As a remark, if two images have different textures, the copying process will be not natural. Poisson editing does not know how to deal with it.

- The process of image completion is tough and long. However, the given results are awesome. The main limitation is the necessity of extra data. The search and acquisition of similar data is not always easy and can come with many restrictions.

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