Image Processing and Computer Vision
The projects

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Non-local mean is a simple denoising method that provide good results.
Non Local mean

Given a pixel at location $p \in \mathbb{N}^2$ We compute the distance of the vector of size 49 corresponding to instensities in a patch of size 7 by 7 around that pixel to all patches in a region around the pixel of size 21 by 21. And compute a weight for each patch:

$$w(p, q) = \frac{1}{\mathcal{Z}} \exp\left(-\frac{||\text{patch}(p) - \text{patch}(q)||^2}{h^2}\right)$$

with $\text{patch}(p) \in \mathbb{R}^{49}$ and $\mathcal{Z}$ an normalization factor. We compute the denoised instensity at location $p$ as the weighted mean of the intensities of the center of the compared patches:

$$NL(I)(p) = \sum_{q} w(p, q) I(q)$$
Circular Minimal Path

We want to find a minimal-cost path (with pixel intensity as costs) through an image with the constraint that the end point matches the starting point after wrapping the image. Using the fact that two minimal paths never cross each other we can get an efficient algorithm using dichotomous search with dynamic programming (similar to Dijkstra):

(a) $l = 1$
(b) $l = 1$
(c) $l = 1$
(d) $l = 0$
(e) $l = 1$
(f) $l = 1$
(g) $l = 1$
(best path: d)
Circular Minimal Path

Applications:
A binary segmentation method based on graph cuts we iterate:

- estimation of the color density distribution using a mixture of gaussian for each of the two regions
- Graph cut with a data term based on the two color distribution and smoothness term that favor cut along edges of the image
Once we segmented the image into foreground/background we estimate the foreground transparency near the contour (matting) using dynamic programming.
Method to detect segments in an image using a statistic criterion to limit the number of parameters
Statistical criterion to measure if the number of aligned gradient orientations in the rectangle would be rare in a random image.
Select a region in the image

Compute an histogram of the pixel intensities with a weight that decrease with the distance to the center of the region.

Weighted histogram of image region around $x$:

$$h(u, c, h, I) = \frac{1}{C_h} \sum_{x,y} k \left( \frac{\|[x, y] - [c_y, c_y]\|^2}{h^2} \right) [I(x, y) = u]$$

with $C_h$ a normalization coefficient such that

$\sum_u h(u, c, h, I) = 1$ and $k$ a smooth decreasing function

with $k(x) = 0$ for $x \geq 1$

thanks to the weighting using $k$, $h(u, c, h, I)$ is a differentiable function of $c$ and we can compute $\frac{\partial h(u, c, h, I)}{\partial c}$
Given a new image, perform a local search for a region with similar weighted histogram.

Similarity is measured using the Bhattacharyya coefficient

\[
S(c_t, h_t) = \sum_u \sqrt{h(u, c_0, h_0, l_0)h(u, c_t, h_t, l_t)}
\]

Using the derivative \( \frac{\partial h(u,c,h,l)}{\partial c} \) we obtain an approximation of \( S \) that can be minimized using the mean shift algorithm.
Shape context: histogram of the relative polar coordinates of all other points.
Match the points with similar shape context using the $\chi^2$ test. Let $(u_1, \ldots, u_n)$ and $(v_1, \ldots, v_n)$ the points of the two shapes, we minimize

$$C_{sc}(\phi) = \sum_{i=1}^{n} C_{sc}(u_i, v_{\phi(i)})$$

we can use bi-partite matching to enforce one-to-one matching
We enforce nearby point to have nearby matchings by adding an additional term

\[ C_{cont} = \sum_{i=2}^{n} \| v_{\phi(i)} - v_{\phi(i-1)} \| \]  (3)

this energy can be minimized efficiently using dynamic programming (a.k.a Viterbi)

without continuity term  with continuity term
cost:

\[ E(\text{cut}) = \sum_{p \in \text{image}} (K_p, D_p(f_p)) + \sum_{\{p,q\} \in N} u_{\{p,q\}} |f_p - f_q| \]  (4)
Stereo Matching and Graph cuts
Stereo Matching and Graph cuts

Construction of the Reduced Graph.

The Reduced Graph.