scikit-image (provisory title)

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scikit-image is an image processing library that implements algorithms and utilities for use in research, education and industry applications. It is released under the liberal Modified BSD open source license, provides a well-documented API in the Python programming language, and is developed by an active, international team of collaborators. In this paper we highlight the advantages of open source to achieve the goals of the scikit-image library, and we showcase several real-world image processing applications that use scikit-image. More information can be found on the project homepage, http://scikit-image.org.

image processing, computer vision, python

Introduction

scikit-image is an image processing....

Mention how ndarray allows us to fit in with rest of eco-system

Parallel & distributed processing via dask

Usage examples

Reducing noise

In this example, we denoise a noisy part of `astronaut`, the picture of the astronaut Eileen Collins. For that end we use three different filters implemented in scikit-image: total variation, bilateral, and wavelets.

These algorithms typically produce “posterized” images, with flat domains separated by sharp edges. It is possible to control the tradeoff between denoising and faithfulness to the original image, controlling the degree of posterization according to the function arguments.

To start this example, the `data` module is imported. It contains the test images available in scikit-image. We also need the function `img_as_float`, which converts the input image into the interval [0, 1]. After that, the variable `img_astro` receives the image `astronaut`, and we obtain a piece of that image. Then, we use the function `random_noise` from the module `util` to generate a noisy version of `img_astro`, according to a stablished value for sigma.

```
from skimage import data, img_as_float
from skimage.util import random_noise

img_astro = img_as_float(data.astronaut())
img_astro = img_astro[0:220, 100:330]

sigma = 0.15
img_noisy = random_noise(img_astro, var=sigma**2)
```

Here `img_noisy` receives the noisy version of `img_astro`. The variance of the random distribution used to generate the noise, represented as `var` in `random_noise`, is defined by the stablished value for sigma squared (`sigma**2`).

Total variation filter

The total variation filter returns an image with minimal total variation norm, while being as close as possible to the initial image. The total variation norm is given as the L1 norm of the image gradient. This filter tends to produce piecewise-constant ("cartoon-like") images.

There are two implementations of total variation filters on scikit-image: split-Bregman [REF: Getreuer, 2012] and Chambolle [REF: Chambolle, 2004]. We use the latter in this example: it is given by the function `denoise_tv_chambolle`, contained in the module `restoration`.

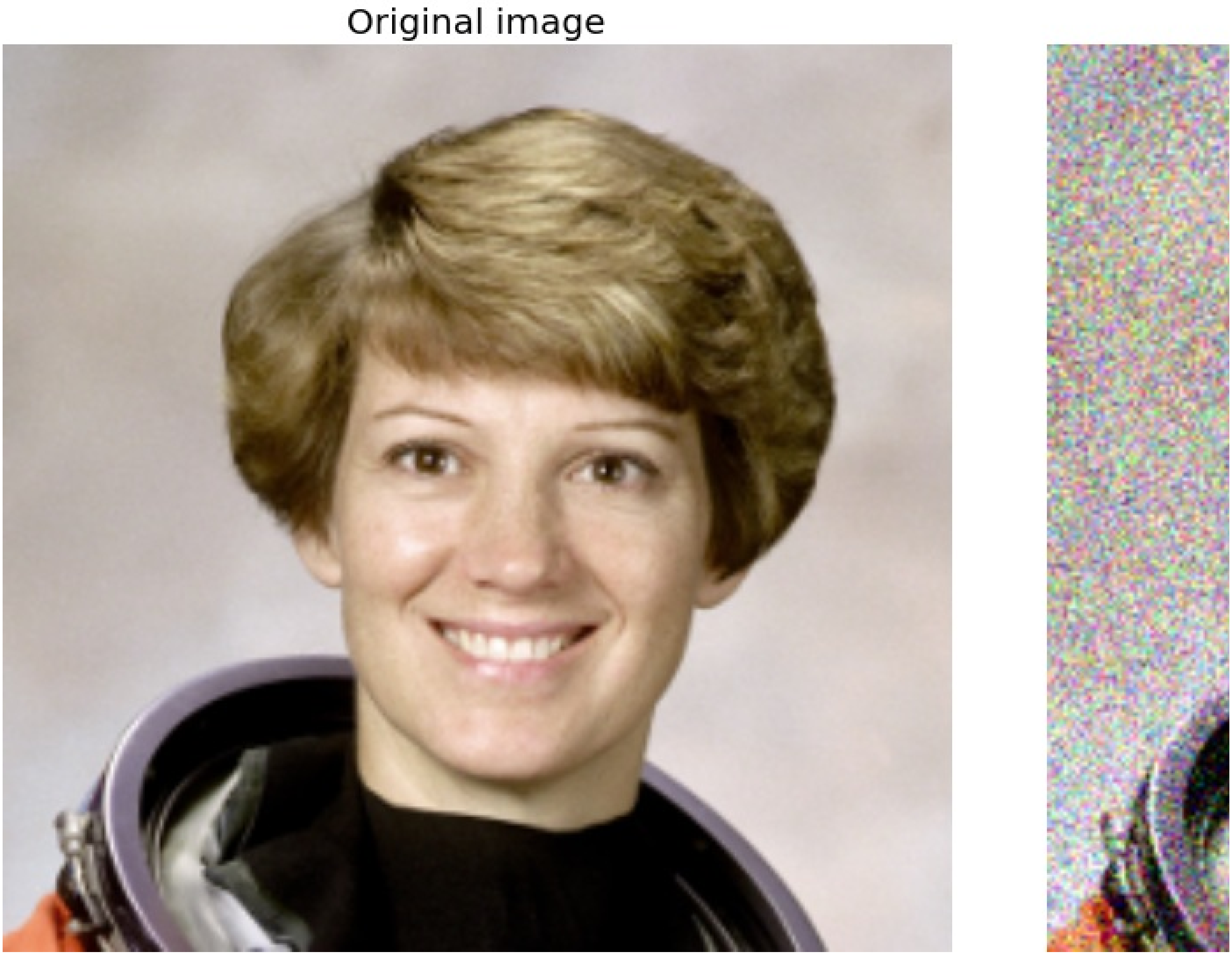
```
from skimage.restoration import denoise_tv_chambolle

img_chamlow = denoise_tv_chambolle(img_noisy,
                                   weight=0.1,
                                   multichannel=True)
img_chamhigh = denoise_tv_chambolle(img_noisy,
                                    weight=0.5,
```

```
                                                multichannel=True)
```

The function `denoise_tv_chambolle` accepts several parameters, in which we used `weight` and `multichannel`: * `weight` represents the denoising weight: the greater the weight, the higher the denoising (at the expense of fidelity to the input image). * `multichannel`, by its turn, enables the option to apply total-variation denoising separately for each color channel. This parameter should receive `True` for color input image; if not, the denoising operation is applied also in channels dimension.

The variables `img_chamlow` and `img_chamhigh` receive `denoise_tv_chambolle` weights equal to `0.1` and `0.5`, respectively. After that we use the module `pyplot` from Matplotlib [REF] to check the denoising results.

```
import matplotlib.pyplot as plt

plt.figure(figsize=(20, 12))

plt.subplot(141)
plt.imshow(img_astro)
plt.title('Original image')
plt.axis('off')

plt.subplot(142)
plt.imshow(img_noisy)
plt.title('Noisy image')
plt.axis('off')

plt.subplot(143)
plt.imshow(img_chamlow)
plt.title('Chambolle filtered image. \n Weight = 0.1')
plt.axis('off')

plt.subplot(144)
plt.imshow(img_chamhigh)
plt.title('Chambolle filtered image. \n Weight = 0.5')
plt.axis('off')

plt.tight_layout()
plt.show()
```



Examples on TV Chambolle's denoising. Note that the higher weight produces a smoother image.

Bilateral filter

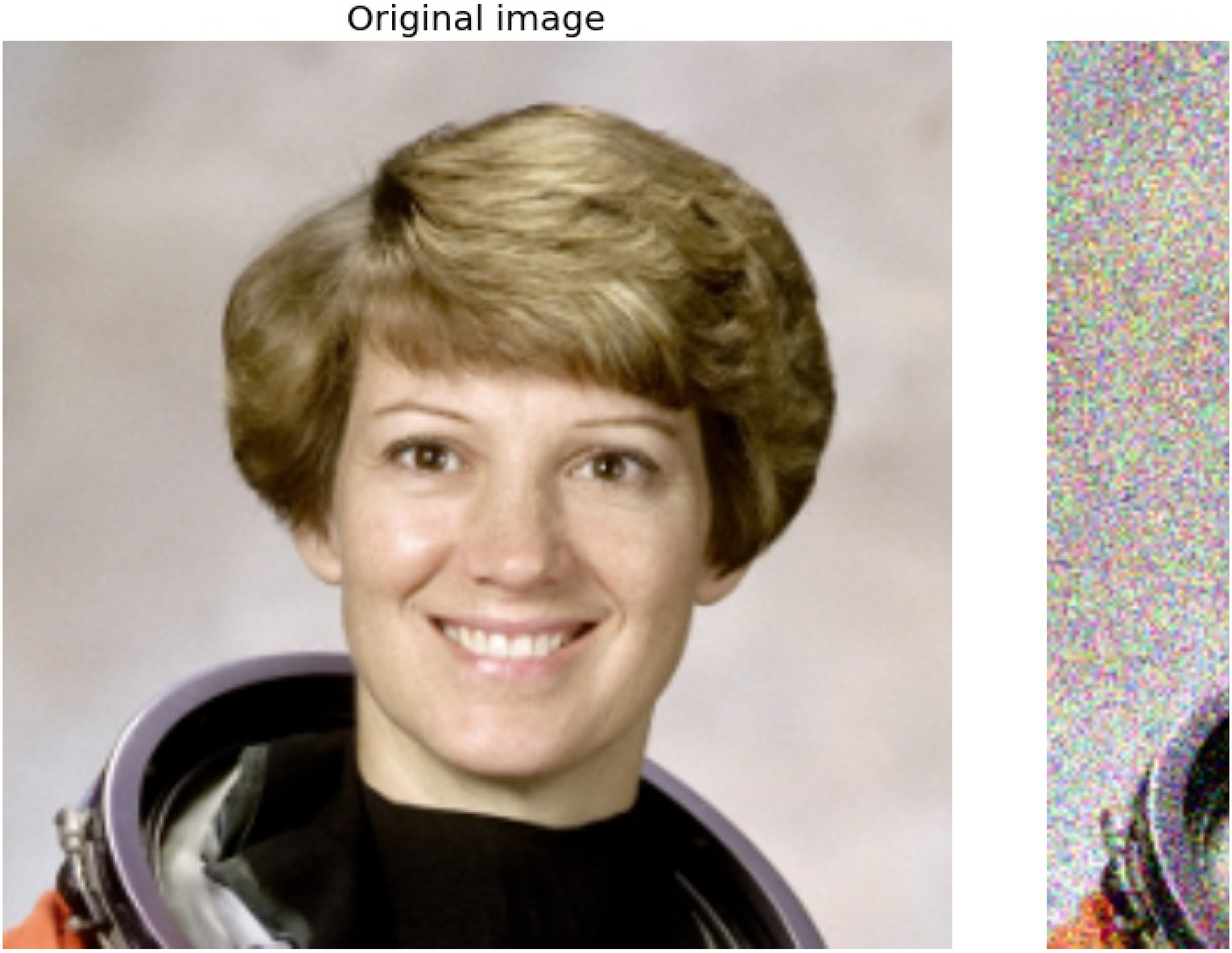
A bilateral filter [REF: Tomasi, Manduchi, 1998] reduces noise while preserving edges. It averages pixels based on their spatial closeness and radiometric similarity. The bilateral filter is implemented by the function `denoise_bilateral`, contained in the module `restoration`.

```
from skimage.restoration import denoise_bilateral

img_billow = denoise_bilateral(img_noisy,
                               sigma_color=0.05,
                               sigma_spatial=5)
img_bilhigh = denoise_bilateral(img_noisy,
                                sigma_color=0.1,
                                sigma_spatial=10)
```

`denoise_bilateral` also accepts several arguments. Here we use `sigma_color` and `sigma_spatial`: * `sigma_color` represents the radiometric similarity, i.e. the standard deviation for color/shade distance. The result is in respect to the interval [0, 1] If it receives the value `None`, the standard deviation of the input image is used. * `sigma_spatial` is the standard deviation for range distance. A larger value results in averaging of pixels with larger spatial differences.

The variable `img_billow` receives smaller `sigma_color` and `sigma_spatial` when compared to `img_bilhigh`. The results are shown using Matplotlib's `pyplot`.

```
import matplotlib.pyplot as plt

plt.figure(figsize=(20, 12))

plt.subplot(141)
plt.imshow(img_astro)
plt.title('Original image')
plt.axis('off')

plt.subplot(142)
plt.imshow(img_noisy)
plt.title('Noisy image')
plt.axis('off')

plt.subplot(143)
plt.imshow(img_billow)
plt.title('Bilateral filtered image. \n\
          $\sigma$ color = 0.05, $\sigma$ spatial = 5')
plt.axis('off')

plt.subplot(144)
plt.imshow(img_bilhigh)
plt.title('Bilateral filtered image. \n\
          $\sigma$ color = 0.1, $\sigma$ spatial = 10')
plt.axis('off')

plt.tight_layout()
plt.show()
```



Examples on bilateral denoising. Higher sigmas produce a smoother image. Compare with TV Chambolle's results.

Detecting corners

Corner detection is used to extract features and infer the contents of an input image. There are several corner detectors implemented on scikit-image. In this example we use one of them, the Harris corner detector [REF], to detect corner points and determine their subpixel position.

First we generate the input image. It is based on an image of a checkerboard, given by the function `data.checkerboard()`. Using the functions `warp` and `AffineTransform` contained in the module `transform`, we can geometrically manipulate the input image.

```
from skimage import data
from skimage.transform import warp, AffineTransform

affine = AffineTransform(scale=(0.8, 1.1),
                         rotation=1,
```

```
                             shear=0.7,
                             translation=(220, 50))
image = warp(data.checkerboard(),
             affine.inverse,
             output_shape=(200, 300))
```

Then we import the functions `corner_harris`, `corner_subpix` and `corner_peaks`, from the module `feature`: * `corner_harris` compute the Harris corner measure response image. * `corner_peaks` find corners in the corner measure response image. * `corner_subpix` determine the subpixel position of corners.

```
from skimage.feature import corner_harris, corner_subpix, corner_peaks

harris_coords = corner_peaks(corner_harris(image))
harris_subpix = corner_subpix(image, harris_coords)
```

Here, `harris_coords` and `harris_subpix` contain the coordinates of each corner found by Harris detector, and their subpixel position. Using Matplotlib's `pyplot` we can check the results. The `plot` function, from `pyplot`, is used to plot the corner points on the original image.

```
import matplotlib.pyplot as plt

fig, ax = plt.subplots(1, 2)
ax[0].imshow(image, cmap='gray')
ax[0].set_title('Original image', fontsize=20)
ax[0].axis((0, 299, 199, 0))
ax[0].axis('off')

ax[1].imshow(image, cmap='gray')
ax[1].plot(harris_coords[:, 1], harris_coords[:, 0],
           '.b', markersize=10)
ax[1].plot(harris_subpix[:, 1], harris_subpix[:, 0],
           '*r', markersize=10)
ax[1].set_title('Harris coordinates and subpixels',
                fontsize=20)
ax[1].axis((0, 299, 199, 0))
ax[1].axis('off')
plt.show()
```

Corners of the original image determined by Harris corner detector. Red stars and blue dots represent the corners and their subpixel position, respectively.

Detecting edges

Panorama Stitching

This example stitches three images into a seamless panorama using several tools in scikit-image, including feature detection, RANdom SAmple Consensus (RANSAC), graph theory, and affine transformations. The images used in this example are available at https://github.com/scikit-image/skimage-tutorials/tree/master/images/pano named `JDW_9*.jpg`.

Load images

The `io` module in scikit-image allows images to be loaded and saved. In this case the color panorama images will be loaded into an iterable `ImageCollection`, though one could also load them individually.

```
from skimage import io
pano_images = io.ImageCollection('/path/to/images/JDW_9*')
```

Panorama source images, taken on the trail to Delicate Arch in Arches National Park, USA. Released under CC-BY 4.0 by Joshua D. Warner.

Feature detection and matching

To correctly align the images, a *projective* transformation relating them is required. 1. Define one image as a *target* or *destination* image, which will remain anchored while the others are warped. 2. Detect features in all three images. 3. Match features from left and right images against the features in the center, anchored image.

In this series, the middle image is the logical anchor point. Numerous feature detection algorithms are available; this example will use Oriented FAST and rotated BRIEF (ORB) features available as `skimage.feature.ORB`[REFERENCE DOI 10.1109/ICCV.2011.6126544 and/or PDF at the authors' site http://www.willowgarage.com/sites/default/files/orb_final.pdf]. Note that ORB requires grayscale images.

```
from skimage.color import rgb2gray
from skimage.feature import ORB, match_descriptors, plot_matches

# Initialize ORB
orb = ORB(n_keypoints=800, fast_threshold=0.05)
keypoints = []
descriptors = []

# Detect features
for image in pano_images:
    orb.detect_and_extract(rgb2gray(image))
    keypoints.append(orb.keypoints)
    descriptors.append(orb.descriptors)

# Match features from images 0 -> 1 and 2 -> 1
matches01 = match_descriptors(descriptors[0], descriptors[1], cross_check
matches12 = match_descriptors(descriptors[1], descriptors[2], cross_check

# Show raw matched features
fig, ax = plt.subplots()
plot_matches(ax, pano_images[0], pano_images[1], keypoints[0], keypoints[
```

```
ax.axis('off');
fig.savefig('./raw_matched.png', dpi=500, pad_inches=0, bbox_inches='tigh
```

Matched ORB keypoints from left and center images to be stitched. Most features line up similarly, but there are a number of obvious outliers or false matches.

Transform estimation

To filter out the false matches observed in [FIGREF PRIOR], RANdom SAmple Consensus (RANSAC) is used [REFERENCE]. RANSAC is a powerful method of rejecting outliers available in `skimage.transform.ransac`. The transformation is estimated using an iterative process based on randomly chosen subsets, finally selecting the model which corresponds best with the majority of matches.

It is important to note the randomness inherent to RANSAC. The results are robust, but will vary slightly every time. Thus, it is expected that the readers' results will deviate slightly from the published figures after this point.

```
from skimage.measure import ransac
from skimage.transform import ProjectiveTransform

# Keypoints from left (source) to middle (destination) images
src = keypoints0[matches01[:, 0]][:, ::-1]
dst = keypoints1[matches01[:, 1]][:, ::-1]

model_ransac01, inliers01 = ransac((src, dst), ProjectiveTransform,
                                   min_samples=4, residual_threshold=1, m

# Keypoints from right (source) to middle (destination) images
src = keypoints2[matches12[:, 1]][:, ::-1]
dst = keypoints1[matches12[:, 0]][:, ::-1]

model_ransac12, inliers12 = ransac((src, dst), ProjectiveTransform,
                                   min_samples=4, residual_threshold=1, m

# Show robust, RANSAC-matched features
fig, ax = plt.subplots()
plot_matches(ax, pano_images[0], pano_images[1],
             keypoints[0], keypoints[1], matches01[inliers01])
ax.axis('off');
```

The best RANSAC transform estimation uses only these keypoints. The outliers are now excluded.

Warp images into place

Before producing the panorama, the correct size for a new canvas to hold all three warped images is needed. The entire size, or extent, of this image is carefully found.

```
from skimage.transform import SimilarityTransform
```

```python
# All three images have the same size
r, c = pano_images[1].shape[:2]

# Note that transformations take coordinates in (x, y) format,
# not (row, column), in order to be consistent with most literature
corners = np.array([[0, 0],
                    [0, r],
                    [c, 0],
                    [c, r]])

# Warp image corners to their new positions
warped_corners01 = model_ransac01(corners)
warped_corners12 = model_ransac12(corners)

# Extents of both target and warped images
all_corners = np.vstack((warped_corners01, warped_corners12, corners))

# The overall output shape will be max - min
corner_min = np.min(all_corners, axis=0)
corner_max = np.max(all_corners, axis=0)
output_shape = (corner_max - corner_min)

# Ensure integer shape with np.ceil and dtype conversion
output_shape = np.ceil(output_shape[::-1]).astype(int)
```

Next, each image is warped and placed into a new canvas of shape `output_shape`.

Translate middle target image

The middle image is stationary, but still needs to be shifted into the center of the larger canvas. This is done with simple translation.

```python
from skimage.transform import warp, SimilarityTransform

offset1 = SimilarityTransform(translation= -corner_min)

# Translate pano1 into place
pano1_warped = warp(pano_images[1], offset1.inverse, order=3,
                    output_shape=output_shape, cval=-1)

# Acquire the image mask for later use
pano1_mask = (pano1_warped != -1)[..., 0]  # Mask == 1 inside image
pano1_warped[~pano1_mask] = 0              # Return background values to
```

Apply RANSAC-estimated transforms

The other two images are warped by `ProjectiveTransform` into place.

```python
# Warp left image
transform01 = (model_ransac01 + offset1).inverse
pano0_warped = warp(pano_images[0], transform01, order=3,
                    output_shape=output_shape, cval=-1)
```

```
pano0_mask = (pano0_warped != -1)[..., 0]  # Mask == 1 inside image
pano0_warped[~pano0_mask] = 0              # Return background values to

# Warp right image
transform12 = (model_ransac12 + offset1).inverse
pano2_warped = warp(pano_images[2], transform12, order=3,
                    output_shape=output_shape, cval=-1)

pano2_mask = (pano2_warped != -1)[..., 0]  # Mask == 1 inside image
pano1_warped[~pano1_mask] = 0              # Return background values to
```

Each image is now correctly warped into the new frame, ready to be combined/stitched together.

Image stitching using minimum-cost path

Because of optical non-linearities, simply averaging these images together will not work. The overlapping areas become significantly blurred. Instead, a minimum-cost path can be found with the assistance of `skimage.graph.route_through_array`. This function allows one to

- start at any point on an array
- find a particular path to any other point in the array
- the path found *minimizes* the sum of values on the path.

The array in this instance is a *cost array*, while the path is the *minimum-cost path*, or MCP. To use this technique we need starting and ending points, as well as a cost array.

Define seed points

```
ymax = output_shape[1] - 1
xmax = output_shape[0] - 1

# Start anywhere along the top and bottom, left of center.
mask_pts01 = [[0,    ymax // 3],
              [xmax, ymax // 3]]

# Start anywhere along the top and bottom, right of center.
mask_pts12 = [[0,    2*ymax // 3],
              [xmax, 2*ymax // 3]]
```

Construct cost array

For optimal results, great care gœs into the creation of the cost array. The function below is designed to construct the best possible cost array. Its tasks are:

1. Start with a high-cost image filled with ones.
2. Use the mask - which defines where the overlapping region will be - to find the distance from the top/bottom edges to the masked area.
3. Reject mostly vertical areas.

4. Give a cost break to areas slightly further away, if the warped overlap is not parallel with the image edges, to ensure fair competition
5. Put the absolute value of the *difference* of the overlapping images in place

[CONSIDER PLACING THIS UTILITY FUNCTION IN AN APPENDIX - IF WE CAN, WE SHOULD ALSO PUT FLOOD FILL THERE]

```
from skimage.measure import label

def generate_costs(diff_image, mask, vertical=True, gradient_cutoff=2.,
                   zero_edges=True):
    """
    Ensures equal-cost paths from edges to region of interest.

    Parameters
    ----------
    diff_image : (M, N) ndarray of floats
        Difference of two overlapping images.
    mask : (M, N) ndarray of bools
        Mask representing the region of interest in ``diff_image``.
    vertical : bool
        Control if stitching line is vertical or horizontal.
    gradient_cutoff : float
        Controls how far out of parallel lines can be to edges before
        correction is terminated. The default (2.) is good for most cases
    zero_edges : bool
        If True, the edges are set to zero so the seed is not bound to
        any specific horizontal location.

    Returns
    -------
    costs_arr : (M, N) ndarray of floats
        Adjusted costs array, ready for use.
    """
    if vertical is not True:  # run transposed
        return tweak_costs(diff_image.T, mask.T, vertical=True,
                           gradient_cutoff=gradient_cutoff).T

    # Start with a high-cost array of 1's
    diff_image = rgb2gray(diff_image)
    costs_arr = np.ones_like(diff_image)

    # Obtain extent of overlap
    row, col = mask.nonzero()
    cmin = col.min()
    cmax = col.max()

    # Label discrete regions
    cslice = slice(cmin, cmax + 1)
    labels = label(mask[:, cslice], background=-1)
```

```
    # Find distance from edge to region
    upper = (labels == 1).sum(axis=0)
    lower = (labels == 3).sum(axis=0)

    # Reject areas of high change
    ugood = np.abs(np.gradient(upper)) < gradient_cutoff
    lgood = np.abs(np.gradient(lower)) < gradient_cutoff

    # Give areas slightly farther from edge a cost break
    costs_upper = np.ones_like(upper, dtype=np.float64)
    costs_lower = np.ones_like(lower, dtype=np.float64)
    costs_upper[ugood] = upper.min() / np.maximum(upper[ugood], 1)
    costs_lower[lgood] = lower.min() / np.maximum(lower[lgood], 1)

    # Expand from 1d back to 2d
    vdist = mask.shape[0]
    costs_upper = costs_upper[np.newaxis, :].repeat(vdist, axis=0)
    costs_lower = costs_lower[np.newaxis, :].repeat(vdist, axis=0)

    # Place these in output array
    costs_arr[:, cslice] = costs_upper * (labels == 1)
    costs_arr[:, cslice] +=  costs_lower * (labels == 3)

    # Finally, place the difference image
    costs_arr[mask] = np.abs(diff_image[mask])

    if zero_edges is True:  # set top & bottom edges to zero
        costs_arr[0, :] = 0
        costs_arr[-1, :] = 0

    return costs_arr


# Use this function
costs01 = generate_costs(pano0_warped - pano1_warped,
                         pano0_mask & pano1_mask)
costs12 = generate_costs(pano1_warped - pano2_warped,
                         pano1_mask & pano2_mask)
```

Find minimum-cost path and masks

Once the cost function is generated, the minimum cost path can be found simply and efficiently.

```
from skimage.graph import route_through_array

# Find the MCP
pts01, _ = route_through_array(costs01, mask_pts01[0], mask_pts01[1],
                               fully_connected=True)
pts01 = np.array(pts01)

# Create final mask for the left image
```

```
mask0 = np.zeros_like(pano0_warped[..., 0], dtype=np.uint8)
mask0[pts01[:, 0], pts01[:, 1]] = 1
mask0 = (label(mask0, connectivity=1, background=-1) == 1)
```

The minimum cost path in blue is the ideal stitching boundary. It stays as close to zero (mid-gray) as possible throughout its path. The background is the cost array, with zero set to mid-gray for better visibility. Note the subtle shading effect of cost reduction below the difference region. Readers' paths may differ in appearance, but are optimal for their RANSAC-chosen transforms.

Because `mask0` is a *final* mask for the left image, it needs to constrain the solution for the right image. This step is essential if there is large overlap such that the left and right images could theoretically occupy the same space. It ensures the MCPs will not cross.

```
# New constraint modifying cost array
costs12[mask0 > 0] = 1

pts12, _ = route_through_array(costs12, mask_pts12[0], mask_pts12[1],
                               fully_connected=True)
pts12 = np.array(pts12)

# Final mask for right image
mask2 = np.zeros_like(mask0, dtype=np.uint8)
mask2[pts12[:, 0], pts12[:, 1]] = 1
mask2 = (label(mask2, connectivity=1, background=-1) == 3)

# Mask for middle image is one of exclusion
mask1 = ~(mask0 | mask2).astype(bool)
```

Blend images together with alpha channels

Most image formats can support an alpha channel as an optional fourth channel, which defines the transparency at each pixel. We now have three warped images and three corresponding masks. These masks can be incorporated as alpha channels to seamlessly blend them together.

```
# Convenience function for alpha blending
def add_alpha(img, mask=None):
    """
    Adds a masked alpha channel to an image.

    Parameters
    ----------
    img : (M, N[, 3]) ndarray
        Image data, should be rank-2 or rank-3 with RGB channels
    mask : (M, N[, 3]) ndarray, optional
        Mask to be applied. If None, the alpha channel is added
        with full opacity assumed (1) at all locations.
    """
    from skimage.color import gray2rgb
    if mask is None:
```

```
        mask = np.ones_like(img)

    if img.ndim == 2:
        img = gray2rgb(img)

    return np.dstack((img, mask))

# Applying this function
left_final = add_alpha(pano0_warped, mask0)
middle_final = add_alpha(pano1_warped, mask1)
right_final = add_alpha(pano2_warped, mask2)
```

Matplotlib[REFERENCE]'s `imshow` supports alpha blending, but the default interpolation mode causes edge effects. For combination into our final result, interpolation is disabled.

```
fig, ax = plt.subplots(figsize=(12, 12))

# Turn off matplotlib's interpolation
ax.imshow(left_final, interpolation='none')
ax.imshow(middle_final, interpolation='none')
ax.imshow(right_final, interpolation='none')

ax.axis('off')
fig.tight_layout()
fig.show()
```

The final, seamlessly stitched panorama.