scikit-image: Image processing in Python

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ABSTRACT

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.

Keywords: image processing, reproducible research, education, visualization

INTRODUCTION

In our data-rich world, images represent a significant subset of all measurements made. Examples include DNA microarrays, microscopy slides, astronomical observations, satellite maps, robotic vision capture, synthetic aperture radar images, and higher-dimensional images such as 3-D magnetic resonance or computed tomography imaging. Exploring these rich data sources requires sophisticated software tools that should be easy to use, free of charge and restrictions, and able to address all the challenges posed by such a diverse field of analysis.

This paper describes scikit-image, a collection of image processing algorithms implemented in the Python programming language by an active community of volunteers and available under the liberal BSD Open Source license. The rising popularity of Python as a scientific programming language, together with the increasing availability of a large eco-system of complementary tools, make it an ideal environment in which to produce an image processing toolkit.

The project aims are:

1. *To provide high quality, well-documented and easy-to-use implementations of*

common image processing algorithms.

Such algorithms are essential building blocks in many areas of scientific research, algorithmic comparisons and data exploration. In the context of reproducible science, it is important to be able to inspect any source code used for algorithmic flaws or mistakes. Additionally, scientific research often requires custom modification of standard algorithms, further emphasizing the importance of open source.

2. *To facilitate education in image processing.*

   The library allows students in image processing to learn algorithms in a hands-on fashion by adjusting parameters and modifying code. In addition, a `novice` module is provided, not only for teaching programming in the "turtle graphics" paradigm, but also to familiarize users with image concepts such as color and dimensionality. Furthermore, the project takes part in the yearly Google Summer of Code program (Google, 2004), where students learn about image processing and software engineering through contributing to the project.

3. *To address industry challenges.*

   High quality reference implementations of trusted algorithms provide industry with a reliable way of attacking problems, without having to expend significant energy in re-implementing algorithms already available in commercial packages. Companies may use the library entirely free of charge, and have the option of contributing changes back, should they so wish.

GETTING STARTED

One of the main goals of scikit-image is to make it easy for any user to get started quickly–especially users already familiar with Python's scientific tools. To that end, the basic image is just a standard NumPy array, which exposes pixel data directly to the user. A new user can simply the load an image from disk (or use one of scikit-image's sample images), process that image with one or more image filters, and quickly display the results:

```
from skimage import data, io, filter

image = data.coins()   # or any NumPy array!
edges = filter.sobel(image)
io.imshow(edges)
```

The above demonstration loads `data.coins`, an example image shipped with scikit-image. For a more complete example, we import NumPy for array manipulation and matplotlib for plotting. At each step, we add the picture or the plot to a matplotlib figure shown in Figure 1.

```
import numpy as np
import matplotlib.pyplot as plt
```

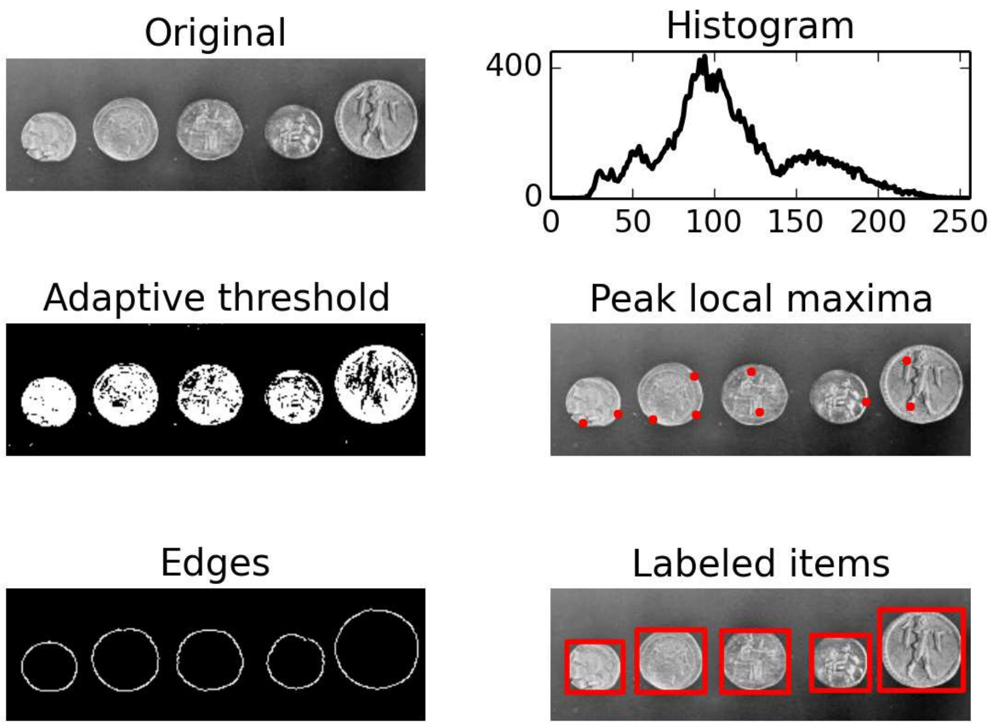

Figure 1. Illustration of several functions available in scikit-image: adaptive threshold, local maxima, edge detection and labels. The use of NumPy arrays as our data container also enables the use of NumPy's built-in `histogram` function.

```
# Load a small section of the image.
image = data.coins()[0:95, 70:370]

fig, axes = plt.subplots(ncols=2, nrows=3,
                         figsize=(8, 4))
ax0, ax1, ax2, ax3, ax4, ax5  = axes.flat
ax0.imshow(image, cmap=plt.cm.gray)
ax0.set_title('Original', fontsize=24)
ax0.axis('off')
```

Since the image is represented by a NumPy array, we can easily perform operations such as building an histogram of the intensity values.

```
# Histogram.
values, bins = np.histogram(image,
                            bins=np.arange(256))

ax1.plot(bins[:-1], values, lw=2, c='k')
ax1.set_xlim(xmax=256)
ax1.set_yticks([0, 400])
ax1.set_aspect(.2)
ax1.set_title('Histogram', fontsize=24)
```

To divide the foreground and background, we threshold the image to produce a binary image. Several threshold algorithms are available. Here, we employ `filter.threshold_adaptive` where the threshold value is the weighted mean for the local neighborhood of a pixel.

```
# Apply threshold.
from skimage.filter import threshold_adaptive

bw = threshold_adaptive(image, 95, offset=-15)

ax2.imshow(bw, cmap=plt.cm.gray)
ax2.set_title('Adaptive threshold', fontsize=24)
ax2.axis('off')
```

We can easily detect interesting features, such as local maxima and edges. The function `feature.peak_local_max` can be used to return the coordinates of local maxima in an image.

```
# Find maxima.
from skimage.feature import peak_local_max

coordinates = peak_local_max(image, min_distance=20)
```

```
ax3.imshow(image, cmap=plt.cm.gray)
ax3.autoscale(False)
ax3.plot(coordinates[:, 1],
         coordinates[:, 0], c='r.')
ax3.set_title('Peak local maxima', fontsize=24)
ax3.axis('off')
```

Next, a Canny filter (`filter.canny`) (Canny, 1986) detects the edge of each coin.

```
# Detect edges.
from skimage import filter

edges = filter.canny(image, sigma=3,
                     low_threshold=10,
                     high_threshold=80)

ax4.imshow(edges, cmap=plt.cm.gray)
ax4.set_title('Edges', fontsize=24)
ax4.axis('off')
```

Then, we attribute to each coin a label (`morphology.label`) that can be used to extract a sub-picture. Finally, physical information such as the position, area, eccentricity, perimeter, and moments can be extracted using `measure.regionprops`.

```
# Label image regions.
from skimage.measure import regionprops
import matplotlib.patches as mpatches
from skimage.morphology import label

label_image = label(edges)

ax5.imshow(image, cmap=plt.cm.gray)
ax5.set_title('Labeled items', fontsize=24)
ax5.axis('off')

for region in regionprops(label_image):
    # Draw rectangle around segmented coins.
    minr, minc, maxr, maxc = region.bbox
    rect = mpatches.Rectangle((minc, minr),
                              maxc - minc,
                              maxr - minr,
                              fill=False,
                              edgecolor='red',
                              linewidth=2)
    ax5.add_patch(rect)
```

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

scikit-image thus makes it possible to perform sophisticated image processing tasks with only a few function calls.

LIBRARY CONTENTS

The scikit-image project started in August of 2009 and has received contributions from more than 100 individuals (Ohloh, 2014). The package can be installed from, amongst other sources, the Python Package Index, Continuum Anaconda (Continuum Analytics, 2012), Enthought Canopy (Enthought, Inc, 2014), Python(x,y) (Raybaut, 2014), NeuroDebian (Halchenko and Hanke, 2012) and GNU/Linux distributions such as Ubuntu (Canonical, Ltd., 2004). In March 2014 alone, the package was downloaded more than 5000 times from the Python Package Index (PyPI, 2014).

The package currently contains the following sub-modules:

- color: Color space conversion.
- data: Test images and example data.
- draw: Drawing primitives (lines, text, etc.) that operate on NumPy arrays.
- exposure: Image intensity adjustment, e.g., histogram equalization, etc.
- feature: Feature detection and extraction, e.g., texture analysis, corners, etc.
- filter: Sharpening, edge finding, rank filters, thresholding, etc.
- graph: Graph-theoretic operations, e.g., shortest paths.
- io: Reading, saving, and displaying images and video.
- measure: Measurement of image properties, e.g., similarity and contours.
- morphology: Morphological operations, e.g., opening or skeletonization.
- novice: Simplified interface for teaching purposes.
- restoration: Restoration algorithms, e.g., deconvolution algorithms, denoising, etc.
- segmentation: Partitioning an image into multiple regions.
- transform: Geometric and other transforms, e.g., rotation or the Radon transform.
- viewer: A simple graphical user interface for visualizing results and exploring parameters.

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DATA FORMAT AND PIPELINING

scikit-image represents images as NumPy arrays (van der Walt et al., 2011), the de facto standard for storage of multi-dimensional data in scientific Python. Each array has a dimensionality, such as 2 for a 2-D grayscale image, 3 for a 2-D multi-channel image, or 4 for a 3-D multi-channel image; a shape, such as $(M, N, 3)$ for an RGB color image with M vertical and N horizontal pixels; and a numeric data type, such as `float` for continuous-valued pixels and `uint8` for 8-bit pixels. Our use of NumPy arrays as the fundamental data structure maximizes compatibility with the rest of the scientific Python ecosystem. Data can be passed as-is to other tools such as NumPy, SciPy, matplotlib, scikit-learn (Pedregosa et al., 2011), Mahotas (Coelho, 2013), OpenCV, and more.

Images of differing data-types can complicate the construction of pipelines. scikit-image follows an "Anything In, Anything Out" approach, whereby all functions are expected to allow input of an arbitrary data-type but, for efficiency, also get to choose their own output format. Data-type ranges are clearly defined. Floating point images are expected to have values between 0 and 1 (unsigned images) or -1 and 1 (signed images), while 8-bit images are expected to have values in {0, 1, 2, ..., 255}. We provide utility functions, such as `img_as_float`, to easily convert between data-types.

DEVELOPMENT PRACTICES

The purpose of scikit-image is to provide a high-quality library of powerful, diverse image processing tools free of charge and restrictions. These principles are the foundation for the development practices in the scikit-image community.

The library is licensed under the *Modified BSD license*, which allows unrestricted redistribution for any purpose as long as copyright notices and disclaimers of warranty are maintained (Regents of the University of California, 1999). It is compatible with GPL licenses, so users of scikit-image can choose to make their code available under the GPL. However, unlike the GPL, it does not require users to open-source derivative work (BSD is not a so-called copyleft license). Thus, scikit-image can also be used in closed-source, commercial environments.

The development team of scikit-image is an open community that collaborates on the *GitHub* (the scikit-image team, 2010a) platform for issue tracking, code review, and release management. *Google Groups* (the scikit-image team, 2010b) is used as a public discussion forum for user support, community development, and announcements.

scikit-image complies with the PEP8 coding style standard (van Rossum et al., 2001) and the NumPy documentation format (Gommers and the NumPy developers, 2010) in order to provide a consistent, familiar user experience across the library similar to other scientific Python packages. As mentioned earlier, the data representation used is n-dimensional NumPy arrays, which guarantees universal interoperability within the scientific Python ecosystem. The majority of the scikit-image API is intentionally designed as a functional interface which allows one to simply apply one function to the output of another. This modular approach also lowers the barrier of entry for new contributors, since one only needs to master a small part of the entire library in order to make an addition.

We ensure high code quality by a thorough review process using the pull request interface on GitHub. The source code is mainly written in Python, although certain performance critical sections are implemented in Cython, an optimising static compiler for Python (Behnel et al., 2011). scikit-image aims to achieve full unit test coverage, which is above 85% as of release 0.10 and continues to rise. A continuous integration system (the Travis-CI community, 2012; LEMUR Heavy Industries, 2013) automatically checks each commit for unit test coverage and failures on both Python 2 and Python 3. Additionally, the code is analyzed by flake8 (Cordasco, 2010) to ensure compliance with the PEP8 coding style standards (van Rossum et al., 2001). Finally, the properties of each public function are documented thoroughly in an API reference guide, embedded as Python docstrings and accessible through the official project homepage or an interactive Python console. Short usage examples are typically included inside the docstrings, and new features are accompanied by longer, self-contained example scripts added to the narrative documentation and compiled to a gallery on the project website. We use Sphinx (Brandl and the Sphinx team, 2007) to automatically generate both library documentation and the website.

The development master branch is fully functional at all times and can be obtained from GitHub (the scikit-image developers, 2010). The community releases major updates as stable versions approximately every six months (Wikipedia, 2014). Major releases include new features, while minor releases typically contain only bug fixes. Users are notified about API-breaking changes by deprecation warnings one full major release before they are applied.

USAGE EXAMPLES

Research

Often, a disproportionately large component of research involves dealing with various image data-types, color representations, and file format conversion. scikit-image offers robust tools for converting between image data-types (Microsoft, 1995; the Khronos Group, 2004; Paeth, 1990) and to do file input/output (I/O) operations. Our purpose is to allow investigators to focus their time on research, instead of expending effort on mundane low-level tasks.

The package includes a number of algorithms with broad applications across image processing research, from computer vision to medical image analysis. We refer the reader to the current API documentation for a full listing of current capabilities (the scikit-image team, 2014). In this section we illustrate two real-world usage examples of scikit-image in scientific research.

First, we consider the analysis of a large stack of images, each representing drying droplets containing nanoparticles (see Figure 2). As the drying proceeds, cracks propagate from the edge of the drop to its center. The aim is to understand crack patterns by collecting statistical information about their positions, as well as their time and order of appearance. To improve the speed at which data is processed, each experiment, constituting an image stack, is automatically analysed without human intervention. The contact line is detected by a circular Hough transform (`transform.hough_circle`) providing the drop radius and its center. Then, a smaller concentric circle is drawn (`draw.circle_perimeter`) and used as a mask to extract intensity values from the image. Repeating the process on each image in the stack, collected pixels can be assembled to make a space-time diagram. As a result, a complex stack of images is reduced to a single image summarizing the underlying dynamic process.

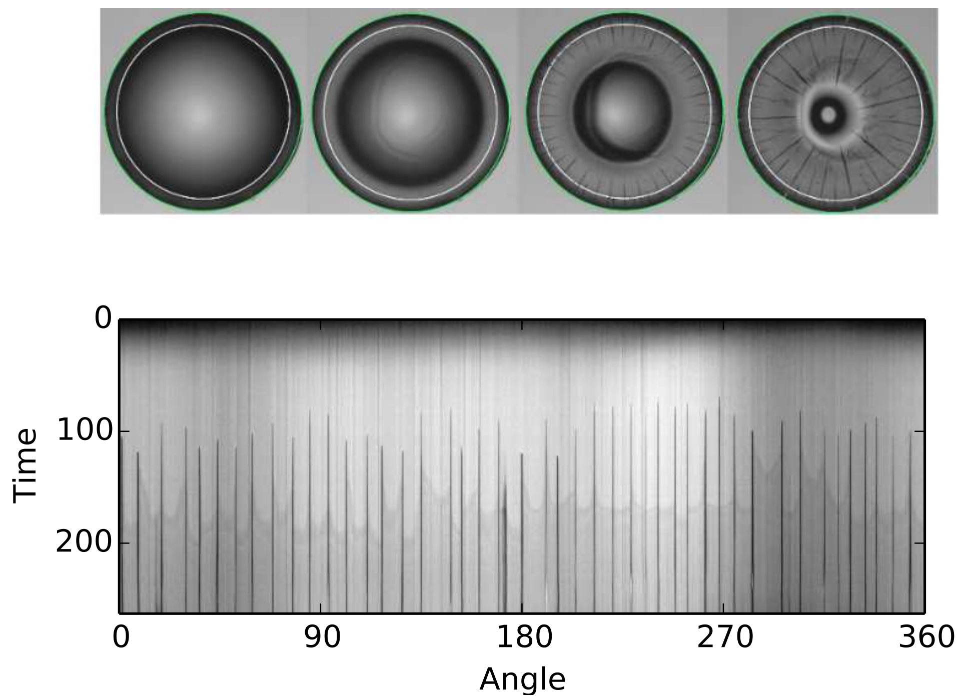

Figure 2. Scikit-image is used to track the propagation of cracks (black lines) in a drying colloidal droplet. The sequence of pictures shows the temporal evolution of the system with the drop contact line, in green, detected by the Hough transform and the circle, in white, used to extract an annulus of pixel intensities. The result shown illustrates the angular position of cracks and their time of appearance.

Next, in regenerative medicine research, scikit-image is used to monitor the regeneration of spinal cord cells in zebrafish embryos (Figure 3).This process has important implications for the treatment of spinal cord injuries in humans (Bhatt et al., 2004; Thuret et al., 2006).

To understand how spinal cords regenerate in these animals, injured cords are subjected to different treatments. Neuronal precursor cells (labeled green in Figure 3, left panel) are normally uniformly distributed across the spinal cord. At the wound site, they have been removed. We wish to monitor the arrival of new cells at the wound site over time. In Figure 3, we see an embryo two days after wounding, with precursor cells beginning to move back into the wound site (the site of minimum fluorescence). The `measure.profile_line` function measures the fluorescence along the cord, directly proportional to the number of cells. We can thus monitor the recovery process and determine which treatments prevent or accelerate recovery.

Education

scikit-image's simple, well-documented application programming interface (API) makes it ideal for educational use, via self-taught exploration or formal training sessions.

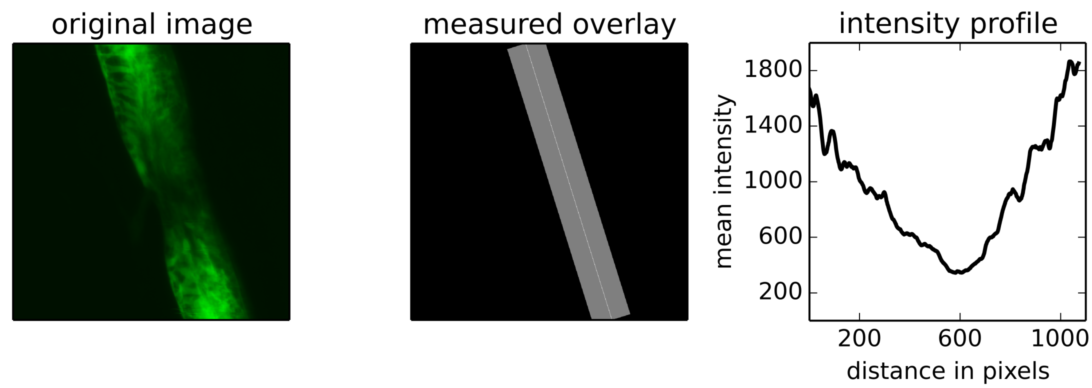

Figure 3. The `measure.profile_line` function being used to track recovery in spinal cord injuries. *Left*: an image of fluorescently-labeled nerve cells in an injured zebrafish embryo. *Middle*: the automatically determined region of interest. The SciPy library was used to determine the region extent, and functions from the scikit-image `draw` module were used to draw it. *Right*: the image intensity along the line of interest, averaged over the displayed width.

The online gallery of examples not only provides an overview of the functionality available in the package but also introduces many of the algorithms commonly used in image processing. This visual index also helps beginners overcome a common entry barrier: locating the class (denoising, segmentation, etc.) and name of operation desired, without being proficient with image processing jargon. For many functions, the documentation includes links to research papers or Wikipedia pages to further guide the user.

Demonstrating the utility and ease-of-use of scikit-image, thirteen-year-old Rishab Gargeya of the Harker School won the Synopsys Silicon Valley Science and Technology Championship using scikit-image in his project, "A software based approach for automated pathology diagnosis of diabetic retinopathy in the human retina" (science-fair.org, 2014).

We have also delivered image processing tutorials using scikit-image at various annual scientific Python conferences, such as EuroSciPy (de Buyl and Pettiaux, 2013), PyData 2012 (PyData organizers, 2012) and SciPy India 2012). Course materials for some of these sessions are found in Haenel et al. (2014) and are licensed under the permissive CC-BY license (Creative Commons, 2013). These typically include an introduction to the package and provide intuitive, hands-on introductions to image processing concepts. The well documented application programming interface (API) along with tools that facilitate visualization contribute to the learning experience, and make it easy to investigate the effect of different algorithms and parameters. For example, when investigating denoising, it is easy to observe the difference between applying a median filter (`filter.rank.median`) and a Gaussian filter (`filter.gaussian_filter`), demonstrating that a median filter preserves straight lines much better.

Finally, easy access to readable source code gives users an opportunity to learn how algorithms are implemented and gives further insight into some of the intricacies of a fast Python implementation, such as indexing tricks and look-up tables.

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Industry

Due to the breadth and maturity of its code base, as well as the its commercial-friendly license, scikit-image is well suited for industrial applications.

BT Imaging (BT Imaging, 2014) designs and builds tools that use photoluminescence (PL) imaging for photovoltaic applications. PL imaging can characterize the quality of multicrystalline silicon wafers by illuminating defects that are not visible under standard viewing conditions. The left panel of Figure 4 shows an optical image of a silicon wafer, and the center panel shows the same wafer using PL imaging. In the right panel, the wafer defects and impurities have been detected through automated image analysis. scikit-image plays a key role in the image processing pipeline. For example, a Hough transform (`transform.hough_line`) finds the wafer edges in order to segment the wafer from the background. scikit-image is also used for feature extraction. Crystal defects (dislocations) are detected using a band-pass filter, which is implemented as a Difference of Gaussians (`filter.gaussian_filter`).

The image processing results are input to machine learning algorithms, which assess intrinsic wafer quality. Solar cell manufacturers can use this information to reject poor quality wafers and charge more for cells that are expected to have high efficiency.

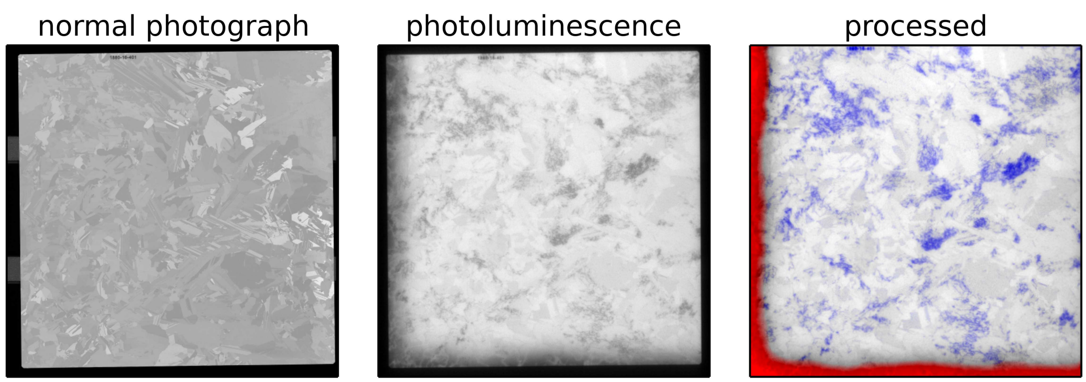

Figure 4. *Left*: An image of an as-cut silicon wafer before it has been processed into a solar cell. *Center*: A PL image of the same wafer. Wafer defects, which have a negative impact solar cell efficiency, are visible as dark regions. *Right*: Image processing results. Defects in the crystal growth (dislocations) are colored blue, while red indicates the presence of impurities.

scikit-image is also applied in a commercial setting for biometric security applications. AICBT Ltd uses multispectral imaging to detect when a person attempts to conceal their identity using a facial mask (AICBT, Ltd., 2014). scikit-image performs file I/O (`io.imread`), histogram equalization (`exposure.equalize_hist`), and aligns a visible wavelength image with a thermal image (`transform.AffineTransform`). The system determines the surface temperature of a subject's skin and detects situations where the face is being obscured.

EXAMPLE: IMAGE REGISTRATION AND STITCHING

This section gives a step-by-step outline of how to perform panorama stitching using the primitives found in scikit-image. The full source code is at https://github.com/

scikit-image/scikit-image-demos.

Data loading

The "ImageCollection" class provides an easy way of representing multiple images on disk. For efficiency, images are not read until accessed.

```
from skimage import io
ic = io.ImageCollection('data/*')
```

Figure 5a shows the Petra dataset, which displays the same facade from two different angles. For this demonstration, we will estimate a projective transformation that relates the two images. Since the outer parts of these photographs do not comform well to such a model, we select only the central parts. To further speed up the demonstration, images are downscaled to 25% of their original size.

```
from skimage.color import rgb2gray
from skimage import transform

image0 = rgb2gray(ic[0][:, 500:500+1987, :])
image1 = rgb2gray(ic[1][:, 500:500+1987, :])

image0 = transform.rescale(image0, 0.25)
image1 = transform.rescale(image1, 0.25)
```

Feature detection and matching

"Oriented FAST and rotated BRIEF" (ORB) features (Rublee et al., 2011) are detected in both images. Each feature yields a binary descriptor; those are used to find the putative matches shown in Figure 5b.

```
from skimage.feature import ORB, match_descriptors

orb = ORB(n_keypoints=1000, fast_threshold=0.05)

orb.detect_and_extract(image0)
keypoints1 = orb.keypoints
descriptors1 = orb.descriptors

orb.detect_and_extract(image1)
keypoints2 = orb.keypoints
descriptors2 = orb.descriptors

matches12 = match_descriptors(descriptors1,
                              descriptors2,
                              cross_check=True)
```

Transform estimation

To filter the matches, we apply RANdom SAmple Consensus (RANSAC) (Fischler and Bolles, 1981), a common method for outlier rejection. This iterative process estimates transformation models based on randomly chosen subsets of matches, finally selecting the model which corresponds best with the majority of matches. The new matches are shown in Figure 5c.

```
from skimage.measure import ransac

# Select keypoints from the source (image to be
# registered) and target (reference image).

src = keypoints2[matches12[:, 1]][:, ::-1]
dst = keypoints1[matches12[:, 0]][:, ::-1]

model_robust, inliers = \
    ransac((src, dst), ProjectiveTransform,
           min_samples=4, residual_threshold=2)
```

Warping

Next, we produce the panorama itself. The first step is to find the shape of the output image by considering the extents of all warped images.

```
r, c = image1.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 the image corners to their new positions.
warped_corners = model_robust(corners)

# Find the extents of both the reference image and
# the warped target image.
all_corners = np.vstack((warped_corners, corners))

corner_min = np.min(all_corners, axis=0)
corner_max = np.max(all_corners, axis=0)

output_shape = (corner_max - corner_min)
output_shape += np.abs(corner_min)
output_shape = output_shape[::-1]
```


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The images are now warped according to the estimated transformation model. Values outside the input images are set to -1 to distinguish the "background".

A shift is added to ensure that both images are visible in their entirety. Note that `warp` takes the *inverse* mapping as input.

```
from skimage.color import gray2rgb
from skimage.exposure import rescale_intensity
from skimage.transform import warp
from skimage.transform import SimilarityTransform

offset = SimilarityTransform(translation=-corner_min)

image0_ = warp(image0, offset.inverse,
               output_shape=output_shape, cval=-1)

image1_ = warp(image1, (offset + model_robust).inverse,
               output_shape=output_shape, cval=-1)
```

An alpha channel is added to the warped images before merging them into a single image:

```
def add_alpha(image, background=-1):
    """Add an alpha layer to the image.

    The alpha layer is set to 1 for foreground
    and 0 for background.
    """
    rgb = gray2rgb(image)
    alpha = (image != background)
    return np.dstack((rgb, alpha))

image0_alpha = add_alpha(image0_)
image1_alpha = add_alpha(image1_)

merged = (image0_alpha + image1_alpha)
alpha = merged[..., 3]

# The summed alpha layers give us an indication of
# how many images were combined to make up each
# pixel.  Divide by the number of images to get
# an average.
merged /= np.maximum(alpha, 1)[..., np.newaxis]
```

The merged image is shown in Figure 5d. Note that, while the columns are well aligned, the color intensities at the boundaries are not well matched.

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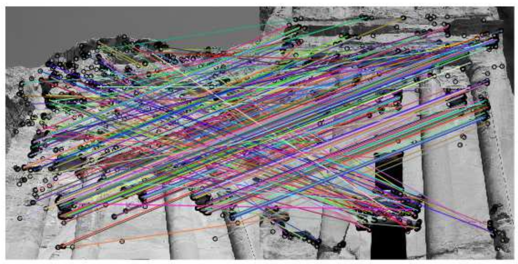
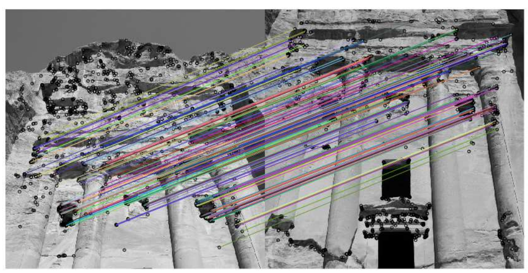
(a) Petra images



(b) ORB binary features



(c) RANSAC-filtered features

(d) Warped & positioned

(e) Final result, combined with Enblend

Figure 5. An example application of scikit-image: image registration and warping to combine overlapping images. (a): Photographs taken in Petra, Jordan by François Malan. License: CC-BY. (b): Putative matches computed from ORB binary features. (c): Matches filtered using RANSAC. (d): The second input frame (*middle*) is warped to align with the first input frame (*left*), yielding the averaged image shown on the right. (e): The final panorama image, registered and warped using scikit-image, blended with Enblend.

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Blending

To blend images smoothly we make use of the open source package Enblend (Dersch and PanoTools contributors, 2010), which in turn employs multi-resolution splines and Laplacian pyramids (Burt and Adelson, 1983b), (Burt and Adelson, 1983a). The final panorama is shown in Figure 5e.

CONCLUSION

scikit-image provides easy access to a powerful array of image processing functionality. Over the past few years, it has seen significant growth in both adoption and contribution, and the team is excited to collaborate with others to see it grow even further, and to establish it the de facto library for image processing in Python.

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