Relating Polarized Light Imaging Data Across Scales

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Polarized light imaging (PLI) ([1, 2]) enables scanning of individual histological human brain sections with two independent setups: a large-area polarimeter (LAP, "object space resolution", which is referred to as "resolution" in the remainder of this abstract: $64 \times 64\,\mu\text{m}^2/\text{px}$) and a polarizing microscope (PM, resolution: $1.6 \times 1.6\,\mu\text{m}^2/\text{px}$). While PM images are of high resolution (HR) containing complex information, the LAP provides low resolution (LR) overview-like data. The information contained in an LR image is a mixture of the information of its HR counterpart ([5]). Each resolution yields valuable information, which multiplies if they are combined.

Image registration algorithms, for example, handle multiple resolutions (1) in case of several modalities with special metrics, and (2) in multi-resolution approaches (e.g. [7]) to increase the stability of the optimization process of automatic image registration. In the latter case, the data is coarsened synthetically. Our goal is to directly relate measured HR to LR data of the same object, avoiding artificial intermediate steps.

All images show the average light intensity, that is transmitted through a thin brain slice ([1, 2]), and depict a region from the human occipital pole. The images were manually segmented and smoothed by a Gaussian kernel suitable for noise reduction and adapted to each resolution.

We selected octave 2 at LR and octave 7 at HR for SURF extraction ([3]), where one octave denotes a decrease in resolution by a factor of 2. Features with corresponding scales were matched with FLANN ([6]). Homography estimation from the resulting feature point pairs used RANSAC ([4]). The homography and a linear interpolation scheme were applied to transfer information from LR to HR and vice versa.

Localization of the HR ROI in the LR ROI is plausible (figure 1(B)), while localization in the LAP image fails, because the matched feature point positions in HR and LR do not correspond. Numerical and feature point matching inaccuracies become evident in figure 1(C).

The experiments were performed with one HR ROI (figure 1(A)), one LAP ROI (figure 1(B)) and one LAP image. We plan to improve the algorithm and to obtain complete HR data sets for further exploration of the method's performance.

Keywords: homography, scale-invariant features, information transfer, polarized light imaging, multi-resolution

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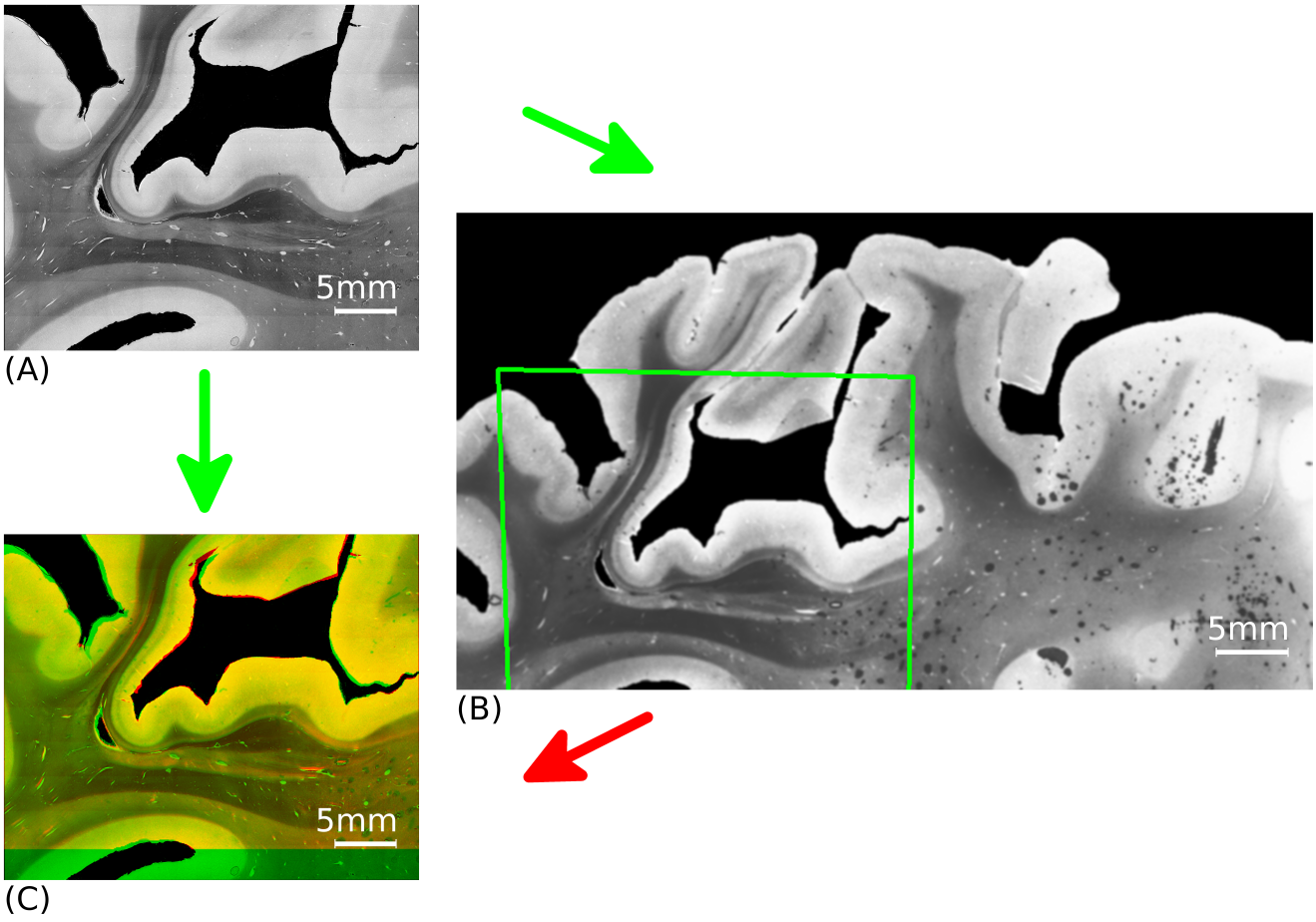

Figure 1: This figure shows input data and results of the experiment. The arrows indicate the flow of information and the color by which it is displayed at its destination. Subfigure (A) shows the down-scaled PM ROI (original size: 20 604 px × 17 157 px). (B) shows the up-scaled LAP ROI (original size: 916 px × 510 px) with estimated PM ROI location (green frame). Note, that only part of the HR ROI is contained in the LR ROI. Also, most of the fine white structures depicted in (A) vanished due to the low resolution of (B). (C) shows the down-scaled overlay image (original size: 20 604 px × 17 157 px) of LR data (enclosed in the green frame in (B)) transferred to HR versus PM ROI data of (A), where HR data is labeled green and transferred LR data is labeled red. HR data and transferred LR data were normalized. Numerical and feature point matching inaccuracies become evident. Also, displacement and distortion compared to HR data is visible.