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Deep Convolutional Feature-Based Fluorescence-to-Color Image Registration

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Background ---- Fluorescence Imaging

- ❖ Fluorescence imaging has been widely utilized in various clinical applications. For example, surgeons use fluorescence imaging to guide tumor resection and sentinel lymph node mapping.
- ❖ Indocyanine green (ICG) is the most popular fluorophores used for fluorescence imaging owing to its low toxicity and high quantum yield.
- ❖ ICG has a peak absorption at 780 nm in the near-infrared (NIR) spectra.

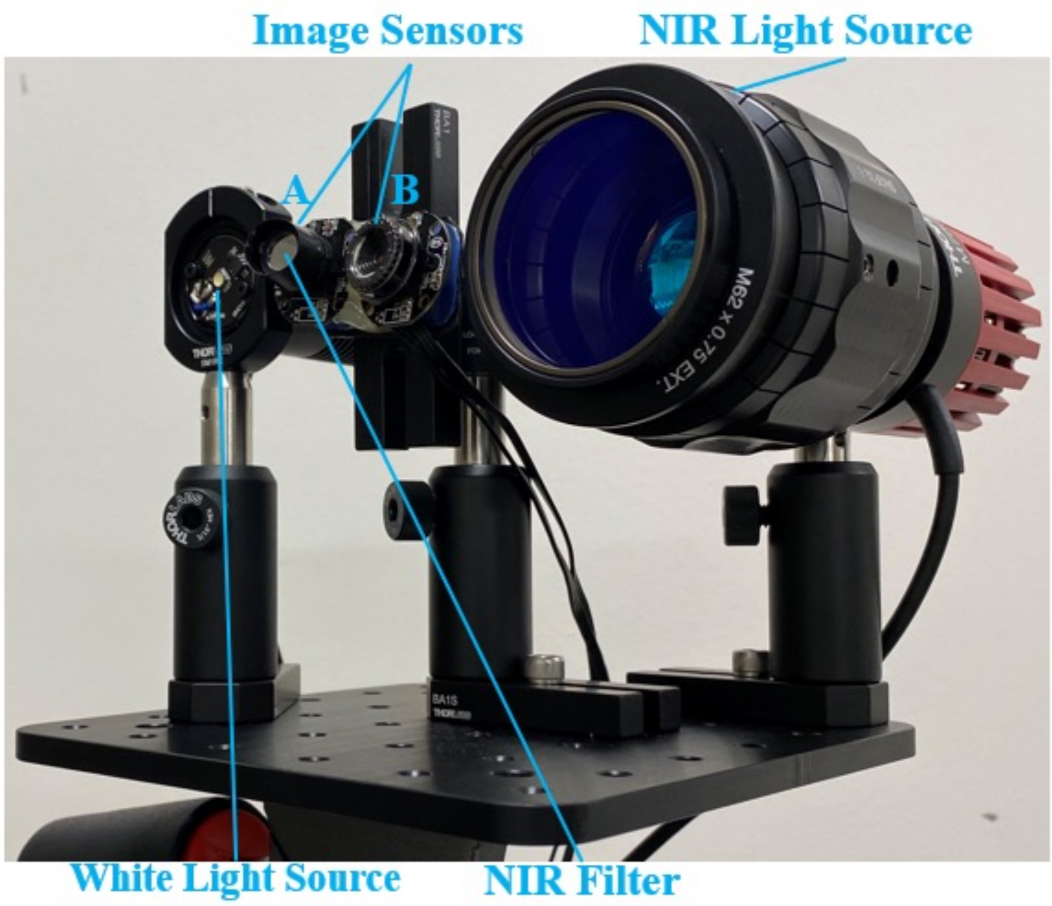
Background ---- Image Registration

- ❖ Feature-based image registration finds features such as edges, corners, lines, curves, regions, templates, and patches from images to establish point-by-point correspondences and derive transformation for image registration.
- ❖ Traditional feature-based image registration relies on algorithms such as Scale-Invariant Feature Transform (SIFT), Speeded Up Robust Features (SURF), Binary Robust Invariant Scalable Keypoints (BRISK), and Oriented FAST and Rotated BRIEF (ORB).
- ❖ Deep learning has achieved excellent performance on extracting image features, so it's used in many computer vision tasks, including image segmentation, image registration, etc.

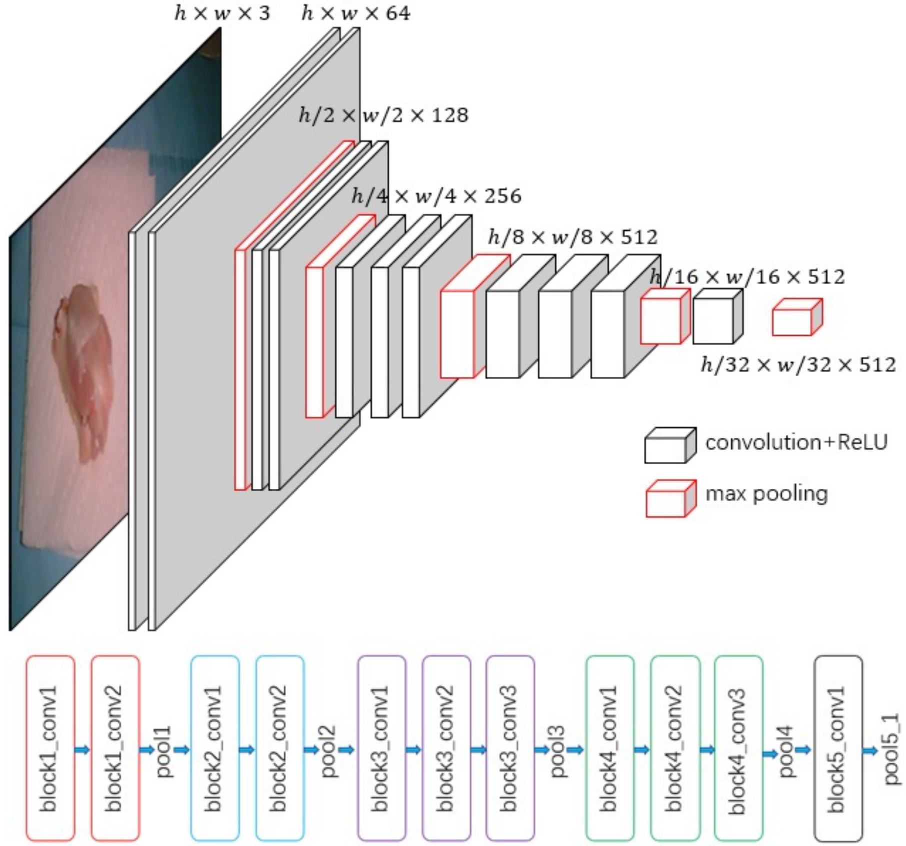
Motivation

- ❖ As a functional imaging modality, NIR fluorescence imaging often does not offer sufficient structural details. Therefore, structural imaging such as color reflectance overlaid with fluorescence imaging represents a superior approach for surgical visualization.
- ❖ We want to improve an existing deep convolutional feature based image registration algorithm for our fluorescence-to-color image registration task.

Methodology ---- System



Methodology ---- VGG16



VGG16

Methodology ---- Feature Descriptor

- If the input of VGG16 is a 224×224×3 RGB image, feature maps of layer ‘pool3’, ‘pool4’ and ‘pool5_1’ have size 28×28×256, 14×14×512, 7×7×512 respectively. The original registration algorithm uses these feature maps to construct the feature descriptor of the input image.
- We found that the resolution of the original feature descriptor is not good enough to obtain accurate keypoint matching. Therefore, we incorporate feature map of layer ‘pool2’. If the input is still a 224×224×3 RGB image, feature map of this layer has size 56×56×128.

Methodology ---- Keypoint Matching

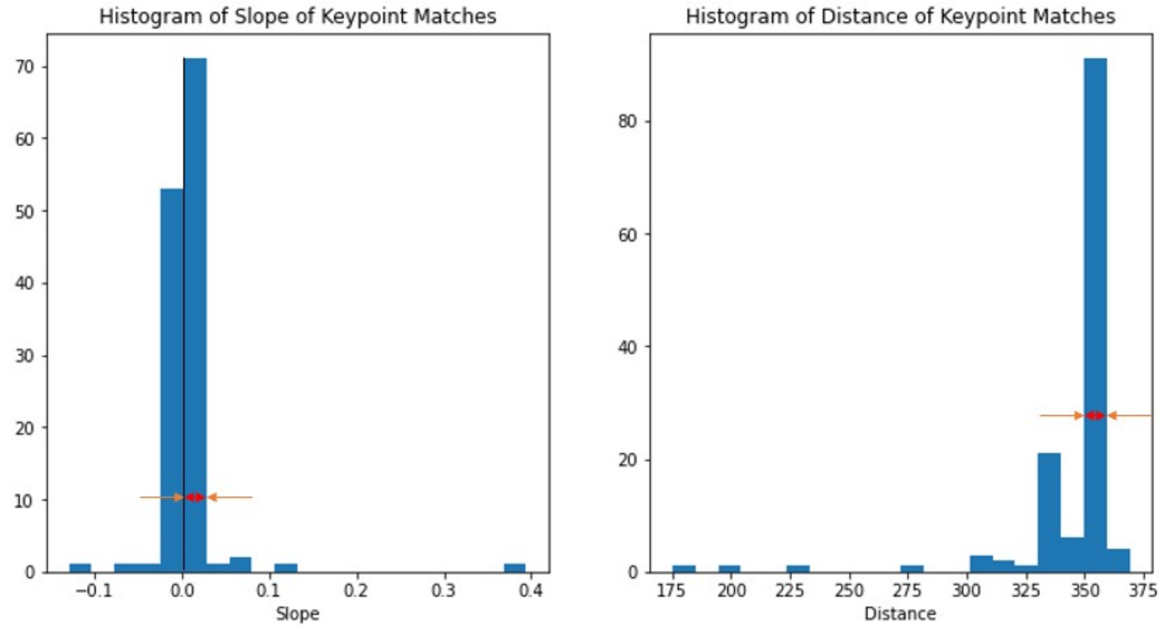
- ❖ Given point x in feature descriptor of the reference image and point y in that of the target image, $d(x, y)$ indicates the distance between x and y in the feature descriptor space.
- ❖ If the following conditions are satisfied:
  - 1) $d(x, y)$ is the smallest of all $d(\cdot, y)$.
  - 2) There does not exist a $d(z, y)$ such that $d(z, y) < \theta \cdot d(x, y)$. θ is a parameter valued greater than 1 and is called the matching threshold.

  then x is matched to y. This is the prematching step.
- ❖ Dynamically adjusting the value of θ can change the keypoint matches in the registration process.

Methodology ---- Matching Filtering

❖ We use a histogram filtering strategy to filter out invalid keypoint matches.

❖ In this way, keypoint matches with big deviations in distance and slope will be filtered out.

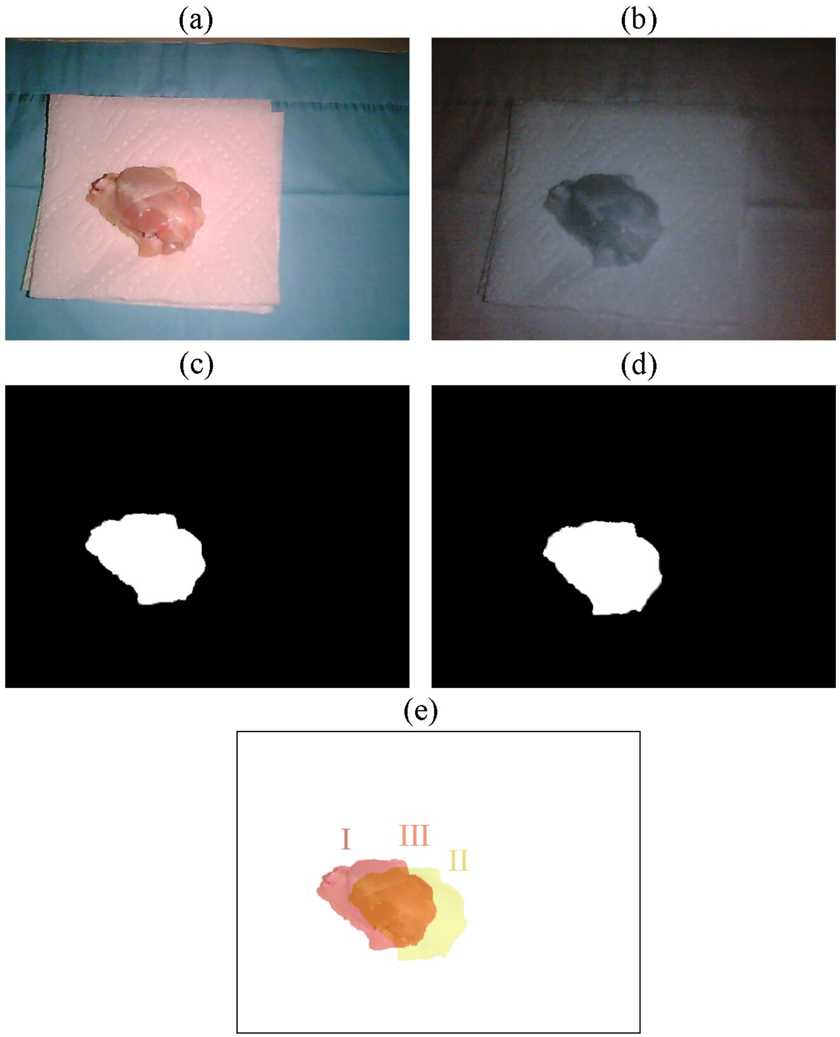


Methodology ---- Evaluation

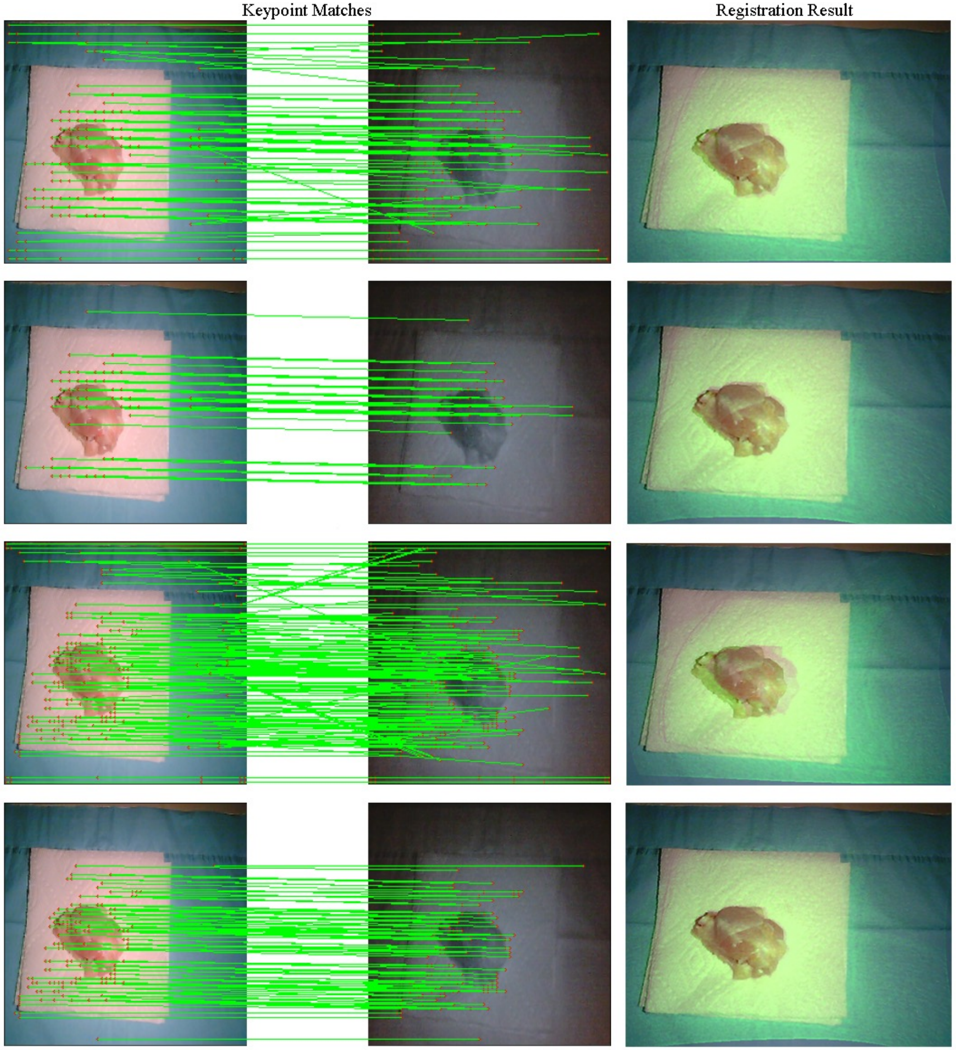
- To show the performance enhancement induced by our two improvements, we provide both qualitative and quantitative results of the original registration algorithm, the original algorithm + keypoint match filtering, the original algorithm + higher-resolution feature descriptor, and the final algorithm with both keypoint match filtering and higher-resolution feature descriptor.
- We qualitatively show registration results of traditional feature based registration algorithms and our modified deep convolutional feature based algorithm.

Methodology ---- Evaluation

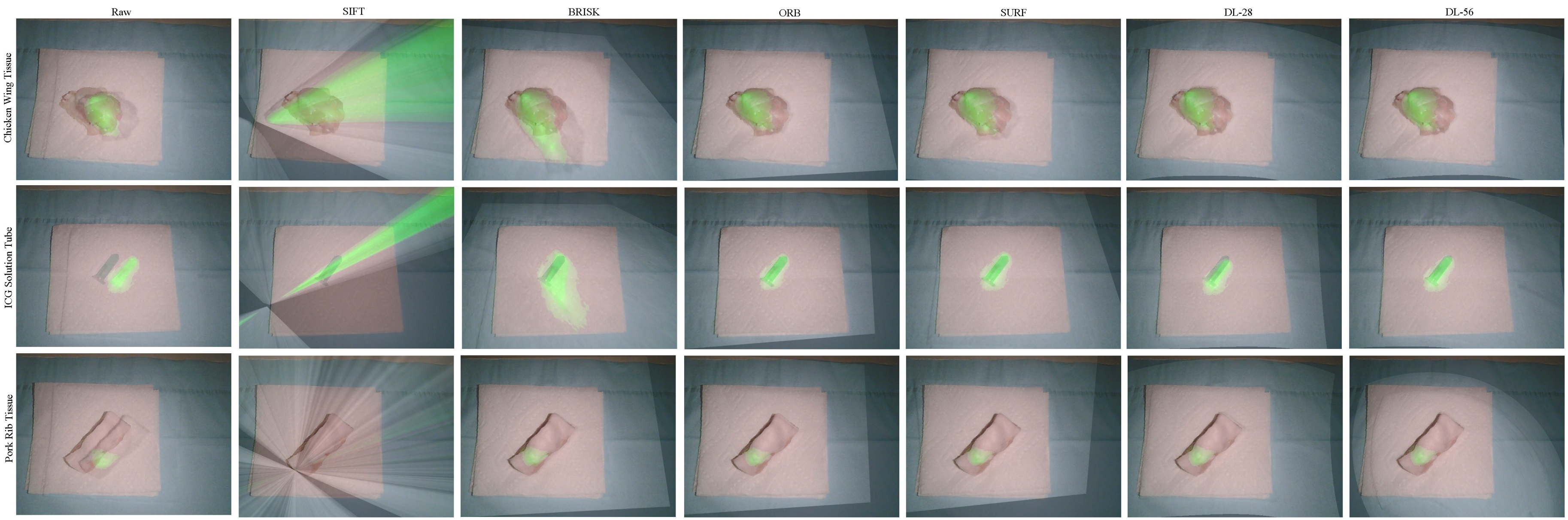
❖ We use the intersection over union (IOU) of object in the reference image and the transformed target image to quantitatively evaluate the performance of registration algorithms.



Result ---- Qualitative Evaluation



Result ---- Qualitative Evaluation



Result ---- Quantitative Evaluation

- ❖ Here, we provide the IOU of the object in the reference image and the transformed target image.
- ❖ We compare the performance of the original algorithm, the original algorithm + keypoint match filtering, the original algorithm + higher-resolution feature descriptor, and the final algorithm with both keypoint match filtering and higher-resolution feature descriptor.

	IOU		
Algorithm	A (Chicken Wing)	B (Tube)	C (Pork Rib)
DL-28_nofilter	0.852	0.032	0.769
DL-28_filter	0.848	0.129	0.816
DL-56_nofilter	0.629	0.124	0.786
DL-56_filter	**0.931**	**0.714**	**0.929**

Discussion

- ❖ Filtering out invalid keypoint matches and using higher-resolution feature descriptor can help to improve the registration performance.
- ❖ Our improved deep convolutional feature based registration algorithm outperforms SIFT and BRISK, and achieves competitive registration performance compared to SURF and ORB.

Conclusion & Future Prospect

- ❖ We have demonstrated the feasibility of deep convolutional feature-based image registration for fluorescence-to-color image registration tasks. Software-hardware codesign was conducted.
- ❖ In the future, we plan to conduct more comprehensive quantitative testing of registration accuracy of deep learning algorithms against other algorithms, and apply the system and method to animal/human studies.

Thanks.