A data-driven approach to feature space selection for robust micro-endoscopic image reconstruction

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Context

Multi-photon microendoscopy allows real-time imaging of cellular-level morphology with high contrast, high penetration depth, minimal phototoxicity and limited sensitivity to the diffusion of biological materials [Duc15]. However, the acquisition of large tissue areas requires a process of multi-view reconstruction from a sequence of low-field-of-view images. Noise, illumination changes and geometric distortions induced by hand motion and optics are making the visual matching of said images a challenging task for reconstruction. In this article, we propose a new on-line image feature space selection strategy for displacement field estimation.

Visual matching using convex optimization

Given a small enough deformation or hand displacement between two consecutive images, we want to identify a geometric transform \( W(x, \theta) \) such that:

\[
I(x, t + \theta t) = I(W(x, \theta), t)
\]

Image registration then consists in estimating a set of parameters \( \theta \), which satisfy this equation i.e.:

\[
\hat{\theta} = \arg \min_{\theta} \|I(x, t) - I(W(x, \theta), t + \theta t)\|^2
\]

Where objective function \( \xi(\theta) \) is considered convex and smooth enough to provide a good estimation of \( \theta \). However it is not the case with our microendoscopic image data:

Data-driven feature space selection

Suppose there exists a set of image feature spaces \( F(x, \theta) \) for which \( \xi(\theta) \) is actually convex. We could use a linear combination \( \hat{\theta} \)-weighted of said features to define a new cost function:

\[
\hat{\theta}(\theta) = \arg \min_{\theta} \| \xi(\theta) \| = \hat{\theta}
\]

\[
\xi(\theta) = \sum_{k=1}^{n} \|F_k(x) - F_k(W(x, \theta), t + \theta t)\|^2
\]

where \( \hat{\theta} \) are ground truth parameters recovered from brute-force search over the original image domain.

The estimation of feature weighting vector \( \hat{\theta} \) is a key element of our method. We are looking for a sparse solution to reduce computation times and provide safety against redundant feature descriptions. Hence the addition of a L1-norm constraint:

\[
\hat{\theta} = \arg \min_{\theta} \left\{ \| \hat{\theta} \|_1 + \sum_{k=1}^{n} \|F_k(x) - F_k(W(x, \theta), t + \theta t)\|^2 \right\}
\]

In practice the endoscope operator is required to capture a few images for ground truth generation, with brute-force matchings providing the algorithm with \( \hat{\theta} \) samples.

Experimental results

Data: 450x450 low-field images taken with a 250µm fiber endoscope. Image features: scale-variant polynomials and Gabor wavelets. Local optimization: BFGS algorithm.

<table>
<thead>
<tr>
<th>Feature space</th>
<th>MSE</th>
<th>SD</th>
</tr>
</thead>
<tbody>
<tr>
<td>Raw pixel intensity</td>
<td>12.67</td>
<td>± 19.40</td>
</tr>
<tr>
<td>Multi-scale polynomial, ( \alpha = 0.1 )</td>
<td>11.05</td>
<td>± 16.70</td>
</tr>
<tr>
<td>Multi-scale polynomial, ( \alpha = 1.0 )</td>
<td>10.37</td>
<td>± 14.57</td>
</tr>
<tr>
<td>Gabor wavelet basis, ( \alpha = 0.1 )</td>
<td>11.21</td>
<td>± 16.66</td>
</tr>
<tr>
<td>Gabor wavelet basis, ( \alpha = 1.0 )</td>
<td>11.05</td>
<td>± 16.70</td>
</tr>
</tbody>
</table>

Conclusion

- A new feature space selection method for displacement field estimation
- On-line learning of ground truth data from non-optimal global methods