THE PYTHAGOREAN AVERAGES AS GROUP IMAGES IN EFFICIENT GROUPWISE REGISTRATION

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Objective

Recently interest has grown for unbiased groupwise registration in image processing tasks such as:

- Population analyses & Atlas construction
- Multiparametric MRI & Radiotherapy planning

The heterogeneity in the application domains calls for a generic methodology, applicable to both mono- and multimodal datasets.

Following Bhatia et al.\textsuperscript{[1]} we have an algorithm for which the computational complexity scales linearly with respect to the number of images in the group:

\[ D_{AAMI}(I_1 \circ T_{\mu_1}, \ldots, I_n \circ T_{\mu_n}) = \sum_{i=1}^{n} D_{MI}(I_i \circ T_{\mu_i}, I_{A\mu}) \]

where

\[ I_{A\mu}(x) = \frac{1}{n} \sum_{i=1}^{n} I_i \circ T_{\mu_i}(x) \]

However, the fuzziness in the average image can compromise the optimization behavior\textsuperscript{[2]}. Additionally, arithmetic averaging handles range and scale differences poorly. We propose to use the other two Pythagorean averages as mean images:

\[ I_{G\mu}(x) = \sqrt[n]{\prod_{i=1}^{n} I_i \circ T_{\mu_i}(x)} \quad I_{H\mu}(x) = \frac{1}{\prod_{i=1}^{n} T_{\mu_i}(x)} \]

Methods and Materials

Results obtained from monomodal experiments performed on the DIR-LAB and POPI dataset and multimodal experiments on the RIRE dataset. Results are reported as the mean and standard deviation of the mTRE.

<table>
<thead>
<tr>
<th>Method</th>
<th>Mean ± Stdev</th>
</tr>
</thead>
<tbody>
<tr>
<td>MSD</td>
<td>1.25 ± 0.29</td>
</tr>
<tr>
<td>MI</td>
<td>1.21 ± 0.25</td>
</tr>
<tr>
<td>SV</td>
<td>1.32 ± 0.40</td>
</tr>
<tr>
<td>AAMI</td>
<td>1.21 ± 0.25</td>
</tr>
<tr>
<td>GAMI</td>
<td>1.21 ± 0.25</td>
</tr>
<tr>
<td>HAMI</td>
<td>1.21 ± 0.24</td>
</tr>
</tbody>
</table>

\begin{align*}
\text{Method} & \quad \text{Mean} \pm \text{Stdev} \\
\text{MI} & \quad 2.34 \pm 0.81 \\
\text{AAMI} & \quad 3.47 \pm 1.85 \\
\text{GAMI} & \quad 2.47 \pm 0.61 \\
\text{HAMI} & \quad 2.69 \pm 1.27 \\
\end{align*}

Conclusions

We have proposed two alternative dissimilarity metrics based on the geometric and harmonic average images and shown their applicability in mono- and multimodal experiments. Especially in the case of multimodal data we show improved results.

References


\textsuperscript{[2]} Guorong Wu, Hongjian Jia, Qian Wang, and Dinggang Shen, Sharpmean: Groupwise registration guided by sharp mean image and tree-based registration, NeuroImage, vol. 56, no. 4, pp. 1908-1911, 2011.