Unsupervised deep learning to identify markers in OCT of AMD

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Introduction

Robust and sensitive imaging biomarkers remain an unmet medical need in the management of macular disease. Classical OCT biomarkers such as fluid and FFA markers of disease activity. Individual correlation coefficients reached from r=-0.36 to r=0.40 (Table 1). Some markers (Figure) corresponded to known findings such as retinal fluid (a17) or subretinal hyperreflective material (a3), while another strongly predictive marker (a4) did not reveal an obvious link to known morphologic features. In a multivariate regression analysis, the markers achieved good correlation with visual function (R²=0.26 (BCVA) and R²=0.44 (LLVA), Table 2).

Results: Local features

The deep learning system identified 20 distinct (local) A-scan features that correlated well with retinal function and known OCT- and FA- markers of disease activity. Individual correlation coefficients reached from r=0.26 to r=0.44 (LLVA), Table 2).

Results: Global features

On the global level, unsupervised learning resulted in a compact 20-dimensional description of the OCT volume. Correlation with visual function was superior to the A-scan level (multivariate R²=0.29 (BCVA) and 0.46 (LLVA), Table 2), and stable for morphologic descriptors of disease activity.

Conclusion

Unsupervised deep learning enabled an unbiased identification and categorization of clinically important markers in OCT imaging that correlated well with visual acuity. Furthermore, it successfully achieved a compact (20-dim) representation of volumetric OCT data. The presented methodology makes big-data OCT analysis feasible by summarizing relevant imaging biomarkers, while discarding unnecessary information provided in the image.

<table>
<thead>
<tr>
<th>BCVA</th>
<th>LLVA</th>
<th>CRT</th>
<th>IRC</th>
<th>SRF</th>
<th>PED</th>
<th>Lesion area</th>
<th>Leakage area</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.26</td>
<td>0.44</td>
<td>0.65</td>
<td>0.09</td>
<td>0.44</td>
<td>0.20</td>
<td>0.27</td>
<td>0.22</td>
</tr>
<tr>
<td>9.1 ± 7.1</td>
<td>10.3 ± 6.5</td>
<td>10.6 ± 11.0</td>
<td>62 ± 48</td>
<td>333 ± 3.36</td>
<td>300 ± 248</td>
<td>1.2 ± 1.0</td>
<td>1.3 ± 1.0</td>
</tr>
</tbody>
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