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19 Supplemental note 1: Overview of Zellige implementation

20

21 Zellige takes as its input a 3D confocal fluorescence microscopy image $I(x,y,z)$

22 containing one or several surfaces of interest. The aim of the software is to segment all

23 surfaces present in the image, and to extract them in the form of height-maps (**Figure 1**). To

24 this end, Zellige proceeds through two main computational steps. In step 1, the software

25 performs a selection of the putative surface pixels, *i.e.* pixels that likely belong to a surface

26 within the image (**Figure S1A, upper panel**). These putative surface pixels are detected as local

27 maxima of image intensity along the z-axis, after using two independent binary classifiers, one

28 based on pixel contrast and the other one on pixel intensity ('amplitude' and 'Otsu' classifiers,

29 described below). The output of step 1 is a binary classification masks $B(x,y,z)$, which defines

30 the set of selected putative surface pixels in the image volume. In step 2, Zellige performs the

31 reconstruction of the surfaces, taking as input the array $B(x,y,z)$ and using an assembly

32 algorithm analogous to a jigsaw puzzle construction (Figure S1A, lower panel). The main

33 output of step 2 is a list of the height-maps h_1, \dots, h_n of each of the surfaces that have been

34 assembled. Finally, the projections of the image $I(x,y,z)$ localized near each of these height-

35 maps are obtained. The two computational steps of Zellige (step 1 and step 2) are described

36 below in more details.

37

38 **Step 1 – Selection of putative surface pixels (Figure S1A, upper panel).**

39

40 After filtering the image by a 3D gaussian blur (with standard deviations of 2x2x1
41 pixels) to reduce noise artifacts, putative surface pixels are detected as the local maxima of
42 image intensity along the z-axis, that is, the pixels (x,y,z) where the partial derivative $\partial I/\partial z$ of
43 image intensity with respect to z changes sign from positive to negative along the z-axis.
44 However, to decrease the number of false positive among these local maxima, the image is
45 first subjected to a classification scheme combining two independent binary classifiers: the
46 ‘amplitude’ and the ‘Otsu’ classifiers.

47 The amplitude classifier is based on a local contrast indicator that quantifies the
48 saliency of a local intensity maximum detected along the z-axis. Specifically, an amplitude
49 $A(p)>0$ is assigned to each such maximum $p=(x,y,z)$, defined as the peak-to-peak difference
50 between the intensity of the given local maximum p and the intensities of the nearest local
51 intensity minima p_1, p_2 along the z-axis, namely, $A(p) = \max(I(p)-I(p_1), I(p)-I(p_2))$ (see **Figure**
52 **S1B**). A zero amplitude is assigned to all the other (non-local maxima) pixels, and the resulting
53 array $A(x,y,z)$ is normalized to have values between 0 and 255. A binary classifier mask $B_A(x,y,z)$
54 is then defined by setting $B_A(x,y,z) = 1$ if $A(x,y,z) \geq T_A$, and $B_A(x,y,z) = 0$ otherwise, where $0 \leq T_A$
55 ≤ 255 is an adjustable threshold setting the minimum allowed salience of a local maximum to
56 be selected as a putative surface pixel.

57 The Otsu classifier is based on the Otsu method, a popular method of segmentation of
58 an image into two classes of “background” and “foreground” pixels [1]. In Zellige, a set of local
59 Otsu thresholds are estimated on a grid of subvolumes of size 40x40x3 subdividing the image
60 stack. These thresholds are regrouped and smoothed using a 3D gaussian filter (with standard
61 deviations of 5x5x1 pixels) to produce a 3D-array of local Otsu thresholds $T_{otsu,loc}(x,y,z)$. An
62 adjustable global Otsu threshold T_{otsu} is also applied to remove low-lying background pixels.
63 The Otsu binary classifier mask $B_{otsu}(x,y,z)$ is then defined by setting $B_{otsu}(x,y,z)=1$ if $I(x,y,z) \geq$
64 $\max(T_{otsu,loc}(x,y,z), T_{otsu})$, and $B_{otsu}(x,y,z)=0$ otherwise.

65 The two classifiers just described are combined by taking the product (or intersection)
66 mask $B(x,y,z) = B_A(x,y,z)B_{otsu}(x,y,z)$, which defines a pre-selected set of putative surface pixels.
67 This mask is further processed by additional clean-up operations (**Figure S1A upper panel**)
68 designed to i) remove small isolated clusters or ‘islands’ formed by putative surface pixels
69 unlikely to belong to a surface of interest, and ii) to partially fill possible surface holes by
70 applying a final gaussian blur to the mask. In the first operation (island removal), an island is
71 defined as a 4-connected component formed by putative surface pixels within some xy-section
72 of the image, which is of a size smaller or equal than a threshold S_{min} , and is not connected to
73 any other selected maxima lying on one of the neighboring $z+1$ or $z-1$ sections. The minimum
74 tolerated island size S_{min} is an adjustable parameter set by default to 5 pixels. Any cluster of a
75 size $\leq S_{min}$ is removed from the list of surface pixels. The second operation (gaussian blur)
76 depends on two adjustable parameters, namely the gaussian blur radiuses σ_{xy} and σ_z used
77 along xy and z , respectively. After the smoothing, a detection of local maxima along z is
78 performed once more on the mask $B(x,y,z)$, this time without classification; this results in a
79 final binary detection mask $M(x,y,z)$ containing the set of putative surface pixels to be used in
80 step 2.

81

82 **Step 2 - Surface reconstruction by assembly of orthogonal surface elements (Figure S1A,**
83 **lower panel).**

84

85 The assembly of surfaces implemented in Zellige proceeds in two phases. First, within
86 each orthogonal (xz or yz) section of the 3D image, building blocks called *orthogonal surface*
87 *elements* (OSEs) are constructed out of the selected surface pixels. The OSEs correspond to
88 contiguous chains of pixels delineating the profile of some surface intersecting the given
89 orthogonal section. Formally, they are defined as the connected components of a graph G_{OSE}
90 defined on the set of putative surface pixels contained within each orthogonal section, with a
91 neighbor structure imposing contiguity constraints assumed to hold for such a profile
92 **(Figure S1C,D).**

93 The OSEs then serve as base elements in the subsequent process of surface assembly.
94 This process starts with a *surface seed*, defined as an OSE whose size is ranked before the
95 T_{OSE} 'th percentile (where $0 \leq T_{\text{OSE}} \leq 1$ is some adjustable fraction) among the list of OSE sizes
96 ranked in decreasing order (in other words, only the OSEs of sizes ranked among the largest
97 T_{OSE} percents can be used for a surface seed). Starting from a seed, a surface S is assembled
98 sequentially by adding new adjacent OSEs provided they fulfill some graph-matching
99 condition. Briefly, a candidate OSE σ adjacent to the boundary of S is tested by computing two
100 quantities, the overlap $R(S, \sigma)$ and connectivity $C(S, \sigma)$ of σ relative to S , which measure how
101 well the shape of σ matches to the surface boundary **(Figure S1E)**. The OSE σ is then added to
102 the surface if its overlap and connectivity are greater than some adjustable thresholds R_0 and
103 C_0 . The surface S is complete when no OSE matching its boundary can be found. A new surface
104 is then assembled, by choosing a new OSE seed that did not belong to S , and reiterating the
105 above construction. The whole assembly process ends when there is no OSE seed left which
106 does not belong to some surface already constructed. At this point, a list of n' reconstructed
107 surfaces $S_1, \dots, S_{n'}$ has been obtained, not all of which will be retained, however: Surfaces that
108 are too small to be genuine surfaces of interest are first removed; the minimum surface size
109 is set by another adjustable parameter $0 \leq p_{\min} \leq 1$, which defines the minimum fraction of the
110 image's xy field of view that should be covered by a reconstructed surface. In addition, it may
111 happen that two or more among the remaining surfaces are identical, except for a small
112 fraction of the OSEs of which they are composed. When for a pair of surfaces this fraction is
113 smaller than some tolerance value, the surfaces are considered redundant and merged,
114 resulting in one multi-valued height-map in which some positions (x, y) correspond to more
115 than one z -value. After this pruning and merging phase, one is left with a list of $n < n'$ distinct
116 but possibly multi-valued surfaces S_1, \dots, S_n .

117 To increase the robustness to the above construction, Zellige applies it in two rounds:
118 in the first round, OSEs are constructed within xz orthogonal sections, and surfaces are
119 assembled along the y axis using relatively loose assembly parameters $(T_{\text{OSE1}}, R_1, C_1)$. In the
120 second round, each of the surfaces S_1, \dots, S_n assembled in the first round is reconstructed in
121 turn, keeping only the pixels of a given surface. This time however, the OSEs are constructed
122 within yz sections, and the surfaces are assembled along the x axis using more stringent
123 matching constraints $(T_{\text{OSE2}}, R_2, C_2)$, with $T_{\text{OSE2}} < T_{\text{OSE1}}$, $R_2 > R_1$, and $C_2 > C_1$.

124 At the end of the two assembly rounds, the ambiguities still present in the surfaces
125 S_1, \dots, S_n are removed to form a final list of genuine (mono-valued) height-maps h_1, \dots, h_n . This is
126 done for each surface S_i , by replacing the height-values of each multiple point, *i.e.* each

127 position (x,y) at which two or more surface points have been detected, by a single value $h_i(x,y)$,
128 or by no value at all, as follows: i) If two points have been detected at heights z_1 and z_2 that
129 differ by less than 2 (i.e. such that $|z_1-z_2| \leq 2$) in pixel units, these two values are averaged by
130 setting $h_i(x,y)=(z_1+z_2)/2$; iii) In all the other cases, i.e. if more than 2 points have been detected,
131 or if two points have been detected whose heights z_1 and z_2 differ by more than 2, the points
132 detected in S_i at (x,y) are discarded, and no value is ascribed to the height-map h_i at that point.
133

134 Supplemental note 2: Generation of phantom 3D images

135
136 The synthetic images used in this project were generated in MATLAB (The MathWorks)
137 using custom code available our public Gitlab instance: . The phantom 3D image shown in
138 **Figure 2** models a typical stack of confocal images of epithelial and non-epithelial structures.
139 It contains three superimposed surfaces, each constructed using a simple algebraic formula.
140 The surfaces generated are of two types: full surfaces, presenting a homogeneous signal over
141 the entire surface, or surfaces presenting a signal restricted to a polygonal mesh mimicking
142 the mesh of apical cellular junctions of an epithelium observed at its surface. To generate
143 these models, we constructed a height-map $z = h(x,y)$ and a projected image $i_0(x,y)$, both
144 having the same format $W \times H$ (with $W = H = 512$ or 1024). For a full surface, the projection is
145 taken constant, $i_0(x,y) = 1$. For a surface restricted to a mesh, the image $i_0(x,y)$ is defined as the
146 mask of a Voronoi mesh constructed on a set of N points ($100 \leq N \leq 300$) distributed at random
147 in the field of the image. The maps $h(x,y)$ and $i_0(x,y)$ are then used as ground truth (GT) to
148 generate a non-noisy 3D image $I_0(x,y,z)$ with $(0 \leq x \leq W - 1, 0 \leq y \leq H - 1, 0 \leq z \leq D - 1)$ in which
149 a discretized version of the surface is inserted, according to the definition: $I_0(x,y,z) = i_0(x,y)$ if
150 $z = [h(x,y)]$, $I_0(x,y,z) = 0$ otherwise. The image $I_0(x,y,z)$ is then subjected to 3D filtering by a
151 Gaussian filter of a size reflecting the point spread function under the sampling conditions
152 typical of confocal images (standard deviations $2 \times 2 \times 3$ pixels along x , y and z). Finally, a
153 Poissonian random noise is added to the result (modeling the photon noise of the confocal
154 images) to produce a final image $I(x,y,z)$ having a given signal-to-noise ratio (SNR).
155

156 Supplemental note 3: Comparing the reconstructed and ground truth 157 height-maps

158 159 Definition of the ground-truth (GT) height-map

160
161 To evaluate the ability of Zellige to reconstruct surfaces present in a 3D image, we
162 define a ground-truth (GT) height-map, that associates each pixel (x,y) of the surface to its
163 true position in the axial (z) dimension. In the case of phantom images, this GT height-map is
164 known exactly. In the case of 3D biological microscopy images, they were obtained as
165 described in [2] by manual annotation, using the Icy software [3]. In brief, the GT height-maps
166 were generated by first manually marking the regions containing the surface of interest on
167 each z section of the image stack. The localization of the surface in z can be ambiguous, which

168 may lead to the selection of multiple z values for a single (x,y) position. When this is the case,
169 the different z values are averaged.

170 When more than one surface of interest was present in the original 3D image, we
171 repeated the above manual segmentation procedure so as to generate one GT height-map for
172 each surface. The height-map of a given surface of interest reconstructed by Zellige or some
173 other surface extraction software could then be compared quantitatively to the corresponding
174 GT height-map, by computing its root mean square error and its coverage.

175

176 [Root mean square error of the reconstructed height-map](#)

177

178 The Root Mean Square Error (RMSE) is a standard measure of the error made by an
179 estimator of a continuously varying quantity. This error is defined here as the root mean
180 square (or Euclidean) distance between a reconstructed height-map $h(x,y)$ and the ground
181 truth height-map $h_{GT}(x,y)$. Note that neither of these height-maps necessarily covers the entire
182 xy field of the image. In general, one or both of the values $h(x,y)$ and $h_{GT}(x,y)$ remain undefined
183 for some points (x,y) , because no corresponding surface point has been detected or selected.
184 We denote by n_T the number of pixels (x,y) for which both the height-maps $h(x,y)$ and $h_{GT}(x,y)$
185 are defined. In the Zellige implementation, a height-map takes >0 values on the pixels where
186 it is defined, and the value 0 on the pixels where it is undefined. With this convention, the
187 RMSE is defined by the formula:

188

$$189 \text{RMSE} = \{1/n_T \sum_{(x,y)} |h(x,y) - h_{GT}(x,y)|^2\}^{1/2},$$

190

191 where the sum runs over the set of pixels for which $h(x,y)$ and $h_{GT}(x,y)$ are both > 0 . A good
192 quality standard for an efficient surface reconstruction algorithm is to produce a height-map
193 with an RMSE of less than 1 (in pixel units), corresponding to an average accuracy of a fraction
194 of a pixel, i.e. typically subpixel distances between the reconstructed and the GT height-maps.

195

196 [Coverage of the reconstructed height-map](#)

197

198 The coverage of the reconstructed height-map (relative to the corresponding GT height-map)
199 is another measure that must be considered when judging the quality of surface
200 reconstruction. It is defined here as the ratio

201

$$202 \text{Rec} = n_T/n_{GT}$$

203

204 where n_{GT} is the number of pixels of the GT height-map.

205 [Supplemental note 4: Sensitivity Analysis](#)

206

207 [Sensitivity analysis by means of a one-parameter scan](#)

208

209 A sensitivity analysis provides an important test of a surface reconstruction algorithm,
210 by quantifying the influence of the various control parameters on the quality of the
211 reconstruction. The aim here is to determine if and when a small change in the value of a given

212 parameter might have a big impact on the RMSE and the coverage of the reconstructed
 213 surfaces. This analysis proceeds by scanning each control parameter in turn (one at a time)
 214 over its entire working range of values. For each value tested, the surface reconstruction
 215 algorithm is run, and the RMSE and coverage of the reconstructed surface(s) of interest are
 216 computed. As a result of this analysis, the parameters which have the most critical influence
 217 on the results can be identified, as well as those which have little or no effect. The sensitivity
 218 analysis carried out in this study was performed for each control parameter of Zellige in
 219 succession: parameters (T_A , T_{otsu} , S_{min} , σ_{xy} , and σ_z) of the surface pixel selection step, and
 220 parameters (T_{OSE1} , R_1 , C_1 , T_{OSE2} , R_2 , C_2) of the surface assembly step. Results obtained on the
 221 phantom image of **Figure 2** and on the biological 3D images of **Figures 3-6** are described below
 222 (**Figures S2-S6**), and summarized in **Figure 7**.
 223

	Surface	Selection parameters					Construction parameters						RMSE	Coverage
		TA	Totsu	IS min	σ_{XY}	σ_Z	TOSE1	R1	C1	TOSE2	R2	C2		
Phantom	n°1												0.23	1.00
	n°2	16	12	5	4	2	0.9	5	0.8	0.1	10	0.8	0.31	1.00
	n°3												0.56	1.00
Fly	n°1												0.93	0.99
	n°2	6	1	5	5	1	0.7	10	0.8	0.1	5	0.9	0.83	0.96
	n°3												1.25	0.94
	n°4												0.55	0.93
Cochlea	n°1	1	1	5	4	1	0.1	5	0.7	0.1	10	0.8	1.08	1.00
Culture	n°1	23	16	5	4	1	0.9	5	0.9	0.1	5	0.8	0.81	0.98
Organoid	n°1	5	12	5	2	1	0.9	5	0.8	0.1	10	0.8	0.83	1.00
	n°2												1.13	0.88

224 **Table S1:** for each dataset, this table summarizes the manually adjusted control parameters of Zellige used to
 225 extract the surfaces, and the corresponding quantification of the result quality in term of RMSE and coverage.
 226
 227

228 **4-1) Sensitivity analysis on a synthetic image.**

229
 230 The phantom image analysed shown in **Figure 2** is composed of one wavy sinusoidal
 231 surface (surface S1), presenting a homogeneous signal over the entire surface, and two
 232 superimposed surfaces (surfaces S2 and S3) presenting a signal restricted to a Voronoi
 233 polygonal mesh. The two polygonal meshes differ by the mesh size and topography. Surface
 234 S2 is supported by a plane and has inclination but no curvature, while surface S3 is supported
 235 by a paraboloid whose axis is at the center of the field of view. The study of such phantom
 236 images was very useful to develop Zellige by allowing us to test and better understand how to
 237 extract multiple surfaces showing various characteristics (in terms of contrast, texture,
 238 topography, etc) from a 3D image using a single set of control parameters. One next asked if
 239 small variations of one parameter in this manually defined parameter set would prevent the
 240 extraction of some surfaces: how robust is Zellige to parameter variations?
 241

242 *Sensitivity to parameters controlling surface pixel selection*

243

244 The results of the sensitivity analysis with respect to the surface pixel selection step,
245 namely the two classification threshold parameters (T_A , T_{otsu}) and the clean-up parameters
246 (minimum island size S_{min} and smoothing radiuses σ_{xy} and σ_z) are shown in **Figure S2A**.
247 Variations of the parameters T_A , T_{otsu} , and S_{min} in their respective working intervals ($0 \leq T_A, T_{otsu}$
248 ≤ 30 and $0 \leq S_{min} \leq 50$) give rise only to small variations of the RMSE and the coverage of the
249 three reconstructed height-maps. The reconstructions remain of high quality (RMSE < 1 and
250 coverage > 95%) for all tested values of these parameters. Regarding the smoothing
251 parameters (σ_{xy} and σ_z), we observe a notable sensitivity on the reconstruction quality
252 (**Figure S2A**). In the absence of smoothing along xy ($\sigma_{xy} = 0$), the reconstructed surface S 2 and
253 S3 appear rough (with RMSE values much larger than 1) despite a good coverage (close to
254 100%). Thus, a minimum of smoothing in xy appears necessary to reconstruct surfaces
255 presenting a mesh. The surface reconstruction is nevertheless robust as it remains high for a
256 wide range of σ_{xy} values ($1 \leq \sigma_{xy} \leq 7$). For too large values of this parameter ($\sigma_{xy} > 7$), the
257 coverage of surface S3 gradually decreases, which is expected as this surface is strongly
258 inclined away from the center of the field of view. The surface reconstruction is also quite
259 robust against variations of the smoothing radius along the z axis, remaining of high quality
260 for $1 \leq \sigma_z \leq 4$. For higher values of σ_z , the surfaces tend to merge, which results in incomplete
261 reconstructions (low coverage) and poor accuracy (high RMSE). Also, using too large values of
262 σ_z is inadequate for strongly inclined surfaces.

263

264 *Sensitivity to parameters controlling surface assembly*

265

266 The surface reconstruction also depends on parameters controlling the assembly of
267 the orthogonal surface elements (OSE), namely the parameters (T_{OSE1} , C_1 , R_1) and (T_{OSE2} , C_2 , R_2)
268 controlling the fraction of OSE sizes allowed for seeds and the matching constraints required
269 between OSEs and surfaces, during the first and second rounds of surface assembly,
270 respectively. The results of the sensitivity analysis against variations of these parameters is
271 shown in **Figure S2B**. The reconstruction turns out to be very robust to variations of the OSE
272 seed size parameters T_{OSE1} , T_{OSE2} and the connectivity parameters C_1 and C_2 , remaining of high
273 quality except for very stringent values ($T_{OSE1} < 0.2$ and $C_1, C_2 \approx 1$). The quality of the
274 reconstruction appears more sensitive to the parameters controlling the overlap constraint
275 (parameters R_1 and R_2 , see **Figure S2B**). Notably, surfaces that show regions of strong
276 inclination tend to be more difficult to reconstruct using very stringent values (close to 1) of
277 R_1 and R_2 . This is expected since inclined surfaces typically display less overlap between OSEs.
278 It is therefore important to keep this threshold value low enough to build surfaces with a steep
279 slope.

280 In summary, the sensitivity analysis on this phantom image demonstrates the high
281 efficiency and robustness of Zellige to extract multiple surfaces with disparate textures and
282 contrasts, without requiring to know a priori the number or relative positions of the surfaces
283 of interest.

284

285 4-2) Sensitivity analysis on 3D images of biological samples

286

287 *Example 1: pupal fly specimen*

288

289 To examine the robustness of the segmentation by Zellige on biological images, we
290 carried out a sensitivity analysis as described above for the phantom image (**Figure S3**). The
291 sensitivity analysis using this fly specimen is described in details in the main text to emphasize
292 that Zellige can robustly extract multiple surfaces from a complex biological image.

293

294 *Example 2: cochlea specimen*

295

296 Variations in the parameter S_{min} over its entire working interval ($0 \leq S_{min} \leq 50$) result in
297 stable high-quality values of the RMSE (< 1) and the coverage ($> 95\%$) (**Figure S4A**), indicating
298 that this parameter is not essential for this data set. The RMSE and coverage also remain
299 rather stable upon variations of the thresholds (T_A, T_{otsu}) and smoothing parameters (σ_{xy}, σ_z),
300 although the intervals ensuring high quality of the reconstructed surface are more restricted
301 than for the fly sample: $0 \leq T_A \leq 7$, $0 \leq T_{otsu} \leq 8$, $\sigma_{xy} \geq 2$, and $0 \leq \sigma_z \leq 2$. An Otsu threshold that
302 is too high leads to the exclusion of the area of interest in this example, because this region is
303 of low signal intensity (**Figure S4A**). As this surface is supported by an epithelial mesh, an xy
304 smoothing is necessary for accurate reconstruction. In addition, to avoid the fusion of the
305 epithelial surface with the underlying structures forming the mesenchyme, the value of the
306 parameter σ_z should be chosen quite low. Regarding the surface assembly control parameters,
307 the values of the RMSE and coverage of the reconstruction remain of high quality over their
308 entire intervals of variation, except for extreme values of the connectivity parameters (C_1, C_2
309 ≈ 1) which lead to a drop in the overlap values. Thus (unlike the other surface extraction
310 software PreMosa, FastSME and LocalZProjector), Zellige not only makes it possible to
311 segment multiple surfaces, but also permits a surface characterized by low signal intensity and
312 low contrast to be extracted selectively against surrounding structures of potentially higher
313 contrast.

314

315

316

317

318 *Example 3: epithelial cell culture specimen*

319

320 For this image containing a single surface of interest of high roughness, the quality of
321 the reconstructed surface is largely insensitive to variations of the S_{min} parameter, remaining
322 high over the whole interval $0 \leq S_{min} \leq 50$. It may be noted, however, that larger values of S_{min}
323 result in lower RMSE and higher coverage values (**Figure S5A**) (for $S_{min} = 50$, RMSE < 1 and the
324 coverage is $> 99\%$). This is not surprising as this specimen harbors out-of-plane dense spurious
325 signal that becomes eliminated by the Island Search filter. The RMSE and coverage remain
326 rather stable upon variations of the classification thresholds (T_A, T_{otsu}) and the smoothing
327 parameters σ_z (RMSE < 1 and coverage $> 99\%$) (**Figure S5A**). Yet, the reconstruction is more
328 sensitive to variations of the smoothing parameter σ_{xy} , which gives best results for $\sigma_{xy} = 6$
329 (RMSE < 1 and coverage $> 99\%$), while still giving good results around this value (RMSE < 1 ,
330 coverage $> 90\%$). With a few exceptions, the values of the RMSE and coverage are stable to
331 variations of most parameters controlling the reconstruction of surfaces (T_{OSE1}, T_{OSE2}, C_1 and
332 C_2), except for extreme values of the connectivity rates (C_1 or $C_2 \geq 0.95$) (**Figure S5B**). However,
333 the reconstruction does show sensitivity to variations of the overlap parameters R_1 and R_2 that

334 should be kept <30% for best results. This observation is likely explained by the particularly
335 rough texture of the epithelium that leads to matching constraints more difficult to satisfy
336 between OSEs and the reconstructed surface. Unlike other Premosa and FastSME, the
337 approach developed with Zellige also makes it possible to extract rough surfaces with a good
338 robustness. For this particular example, Zellige (through a manual adjustment of the
339 parameters of steps 1 and 2) gives similar results to LocalZprojector (obtained as the best
340 results in a parameter sweep as described in Hebert *et al.* 2021 [2].

341

342 *Example 4: inner ear organoid specimen*

343

344 Similarly to the above analyzed specimens, the RMSE and coverage remain stable upon
345 variations of the classification thresholds (T_A , T_{otsu}) (RMSE ~ 1 and coverage $> 80\%$)
346 (**Figure S6A**). The reconstruction is more sensitive to the smoothing parameter σ_{xy} and σ_z ,
347 which is expected due to the proximity of the two surfaces as well as the presence of regions
348 of high inclination at their boundaries. Indeed, higher smoothing values will tend to blend the
349 two surfaces and prevent their reconstruction: for $\sigma_z > 3$, the surface S1 is not reconstructed
350 (null coverage) and another, chimeric surface is reconstructed instead, which is truly a blend
351 of surfaces S1 and S2, as shown by the RMSE > 2 . With a few exceptions, the values of the
352 RMSE and coverage are stable to variations of most parameters controlling the reconstruction
353 of surfaces (T_{OSE1} , T_{OSE2} , C_1 and C_2), except for extreme values of the connectivity rates (C_1 or
354 $C_2 \geq 0.95$). However, the reconstruction shows sensitivity to variations of the overlap
355 parameters R_1 and R_2 that should be kept <30% for best results (**Figure S6B**). Again, this is
356 expected considering the sharp inclination of the surfaces to be reconstructed at their
357 boundary (where the surfaces touch the substrate). Nonetheless, Zellige makes it possible to
358 robustly reconstruct two superimposed mesh-like surfaces including regions of strong
359 inclination, using the same set of parameters.

360

361 Supplemental note 5: Computational/processing time of Zellige

362

363 Computation time comparison between the various images tested

364

365 The core algorithms implementing the two main computational steps of Zellige
366 (surface pixel selection step and surface assembly step) have linear computational
367 complexities in the image size (**Figure S7**), i.e. both steps require a computation time that
368 grows at most linearly in the number of pixels in the original 3D image. For step 1, this linear
369 complexity results formally from the fact that the surface pixel selection amounts to a fixed
370 number of tests applied sequentially to each pixel in the image. For step 2, linear complexity
371 is less clear at the formal level. However, from a practical point of view this is a consequence
372 of the fact that the number of constructed OSEs is bounded by the number of image pixels (in
373 practice it is much smaller), and that the number of surfaces of interest to reconstruct is
374 typically small. As shown below, in the examples we tested, the surface assembly step turns
375 out to run about an order of magnitude faster than the surface pixel selection step.

376 **Figure S7** shows the execution times for running the surface extraction on the images
377 considered in this study ranged between a few seconds to a few tens of seconds on a standard
378 PC workstation (processor Intel Core i9 2,4 GHz). The computational load of Zellige thus allows
379 the processing of large datasets in reasonable time. For all the images tested, the surface pixel
380 selection step (step 1) is the most computationally costly, taking over >70% of the total
381 execution time. The surface assembly step (step 2) usually runs in a few seconds, and rarely in
382 more than 10s. This step 2 tends to be more computationally demanding for images
383 containing numerous spurious structures surrounding the surface of interest, or when
384 reconstructing a surface having a rough topography (as in the case of the cochlea and culture
385 examples of **Figures 4** and **5**). The computational time of the surface assembly step turns out
386 to be also sensitive to the parameters T_{OSE1} and T_{OSE2} setting the fraction of OSE sizes allowed
387 for the OSE seeds during the two rounds of surface assembly. For values of 60% or more (when
388 a majority of available OSE sizes are allowed as seeds), the computation time of step 2 raises
389 significantly, occasionally reaching times comparable or larger than those of step 1. This is not
390 unexpected since adopting large values for T_{OSE1} and T_{OSE2} means that large sets of OSE seeds
391 have to be incorporated into surfaces before the construction is complete. It is thus
392 advantageous to limit these parameters to values < 50%, which does not affect the quality of
393 surface reconstruction. With this proviso, the most limiting step of Zellige regarding
394 computational time is therefore the surface pixel selection step, which includes the two binary
395 classifications schemes applied (amplitude and Otsu classifications), as well as the
396 morphological clean-up operations embodied in the small island removal and the final
397 gaussian interpolation. Note that the surface selection step essentially consists of a series
398 filtering operations and of sequential pixel testing or computations, all of which could be to a
399 large extent parallelized. The implementation of this step on a parallel platform (e.g. GPU or
400 multi-core processors) might boost the computational time of Zellige sufficiently for real-time
401 applications.

402

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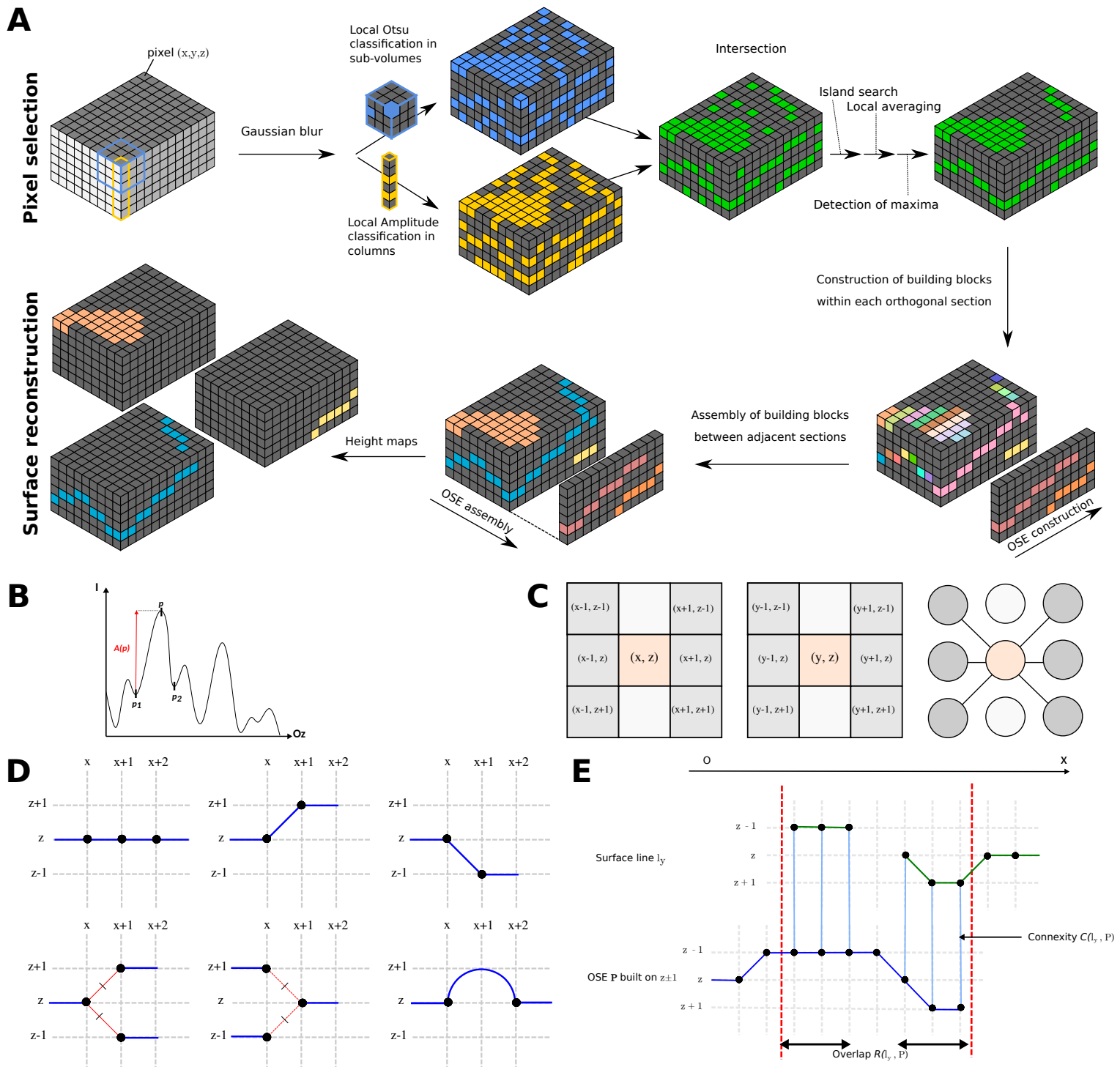
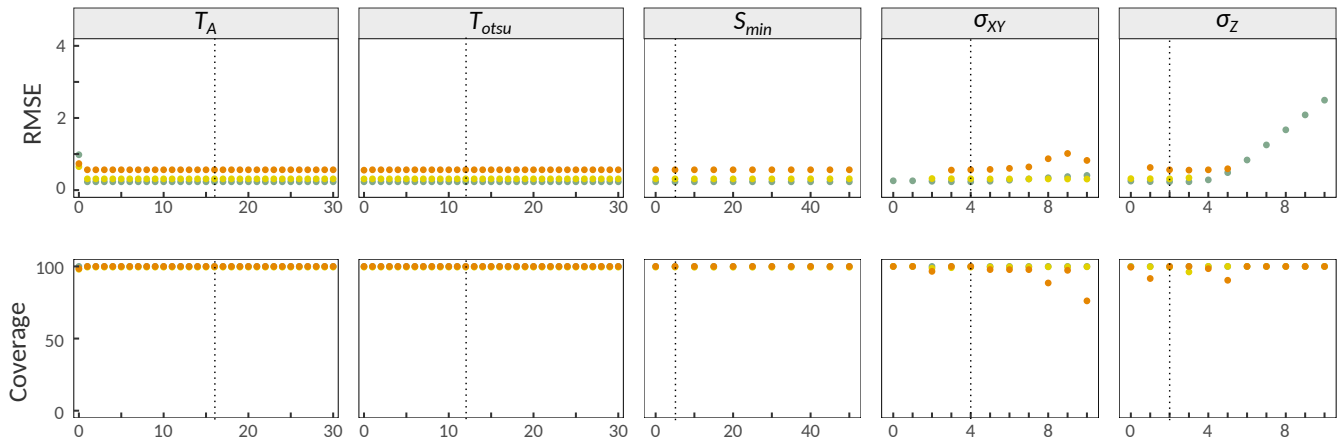


Figure S1. Zellige implementation. **(A)** The two main algorithmic steps of Zellige. Upper part: Surface pixel selection step (step 1). Lower part: Surface assembly step (step 2). **(B)** Determination of the amplitude $A(p)$ of some local maximum p along the z axis, relative to its two closest local minima p_1 and p_2 . **(C, D)** Connectivity rules used to connect putative surface pixels together for the construction of orthogonal surface elements (OSEs). These rules are based on a 6-connectivity relationship defined within each orthogonal (xz or yz) section as shown in (C). This relationship is extended to allow the presence of single straight gaps, while being constrained to forbid the occurrence of forking points. The allowed local neighborhood configurations along an OSE are illustrated in (D) in the case of a construction within xz sections. The OSEs are formally defined as the connected components of the graph G_{OSE} defined by these rules within each orthogonal section. **(E)** Compatibility rules used in the surface assembly step, illustrated here in the case where OSEs have been constructed within xz sections, and assembly proceeds along the y axis. To validate the addition of a new OSE σ constructed within section $y+1$ (in blue) to the surface S under construction, whose intersection with section y is shown (surface line l_y , in green), two quantities are computed: the overlap $R(S, \sigma)$ is defined as the number of pixels of σ that share the x coordinate of some pixel of l_y . The connectivity $C(S, \sigma)$ is defined as the fraction of the overlapping pixels of σ that are 6-connected, in their respective yz section, to the corresponding point of l_y (according to the 6-connectivity relationship shown in C, middle panel). In the depicted example, $R(S, \sigma) = 6$ and $C(S, \sigma) = 6/6 = 1$. The OSE will be added to S if $R(S, \sigma) \geq R_0$ and $C(S, \sigma) \geq C_0$, where R_0 and C_0 are tunable thresholds that set the stringency of the matching condition.

A

Selection Parameters



Surfaces

1

2

3

B

Construction Parameters

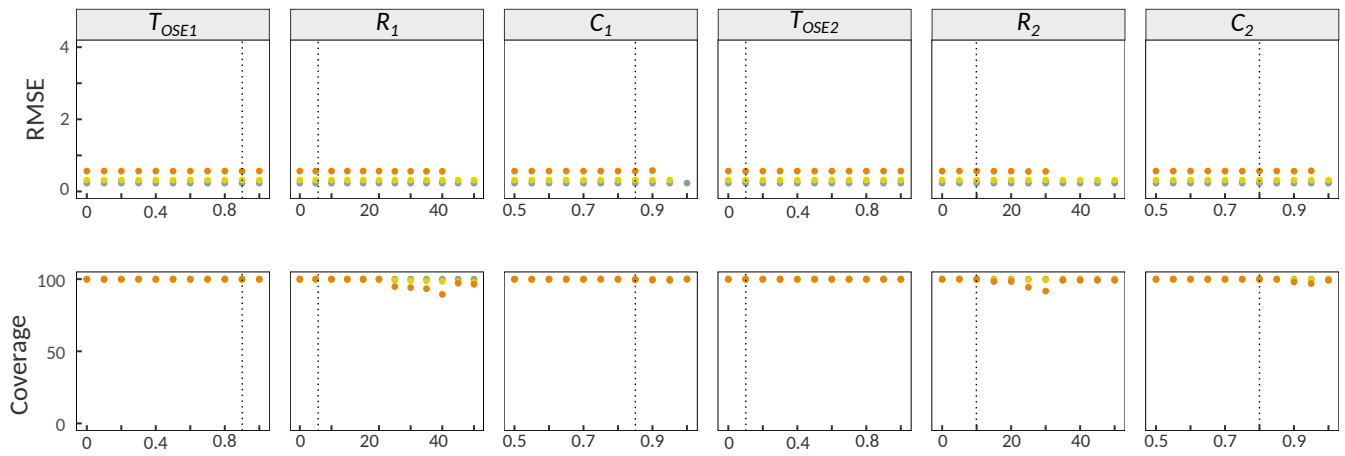


Figure S2. Sensitivity analysis of Zellige on the phantom image. (A) Surface pixel selection parameters. **(B)** Surface assembly parameters. Reference values are indicated by the dashed line.

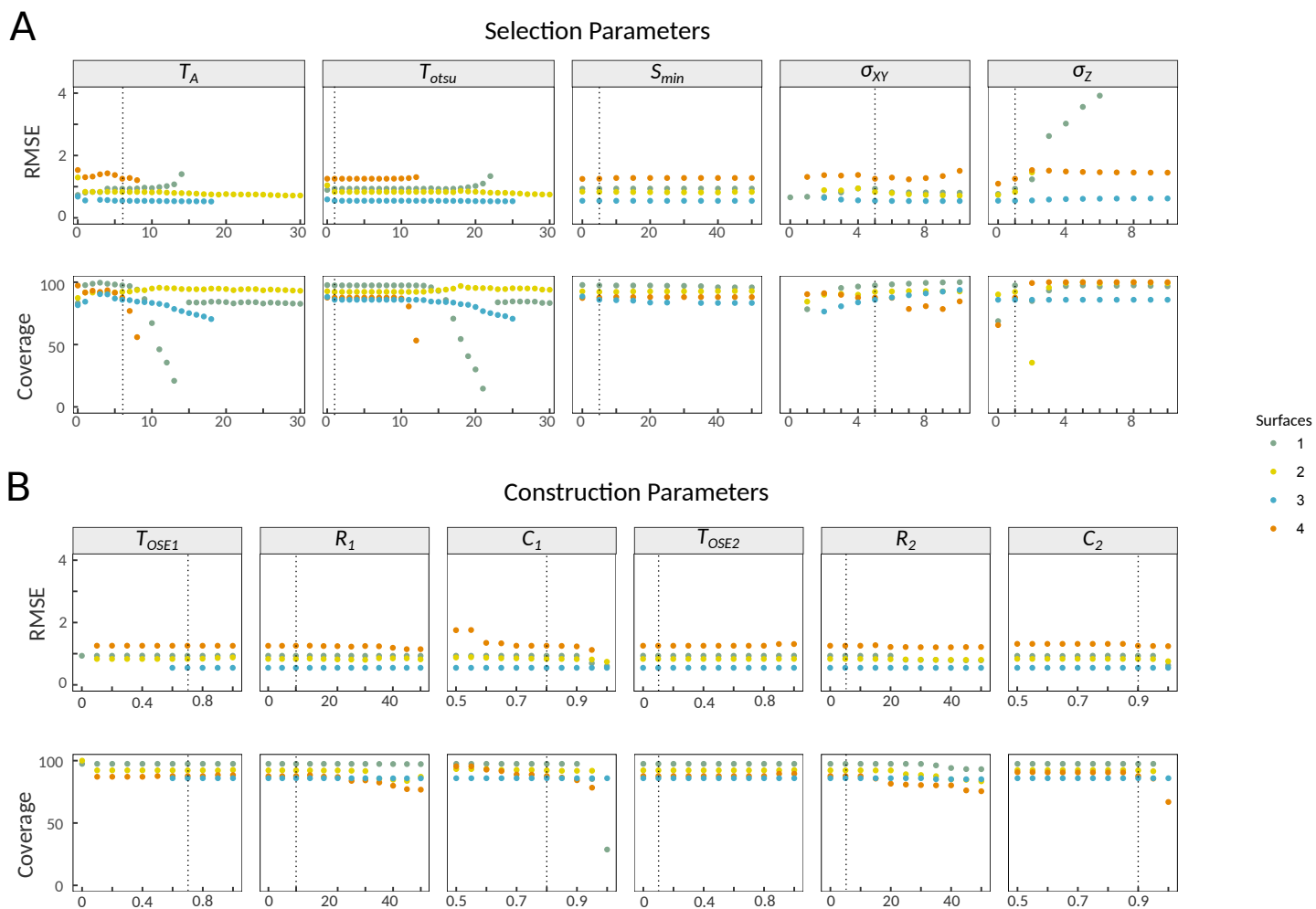


Figure S3. Sensitivity analysis of Zellige on the pupal fly image. (A) Surface pixel selection parameters. **(B)** Surface assembly parameters. Reference values are indicated by the dashed line.

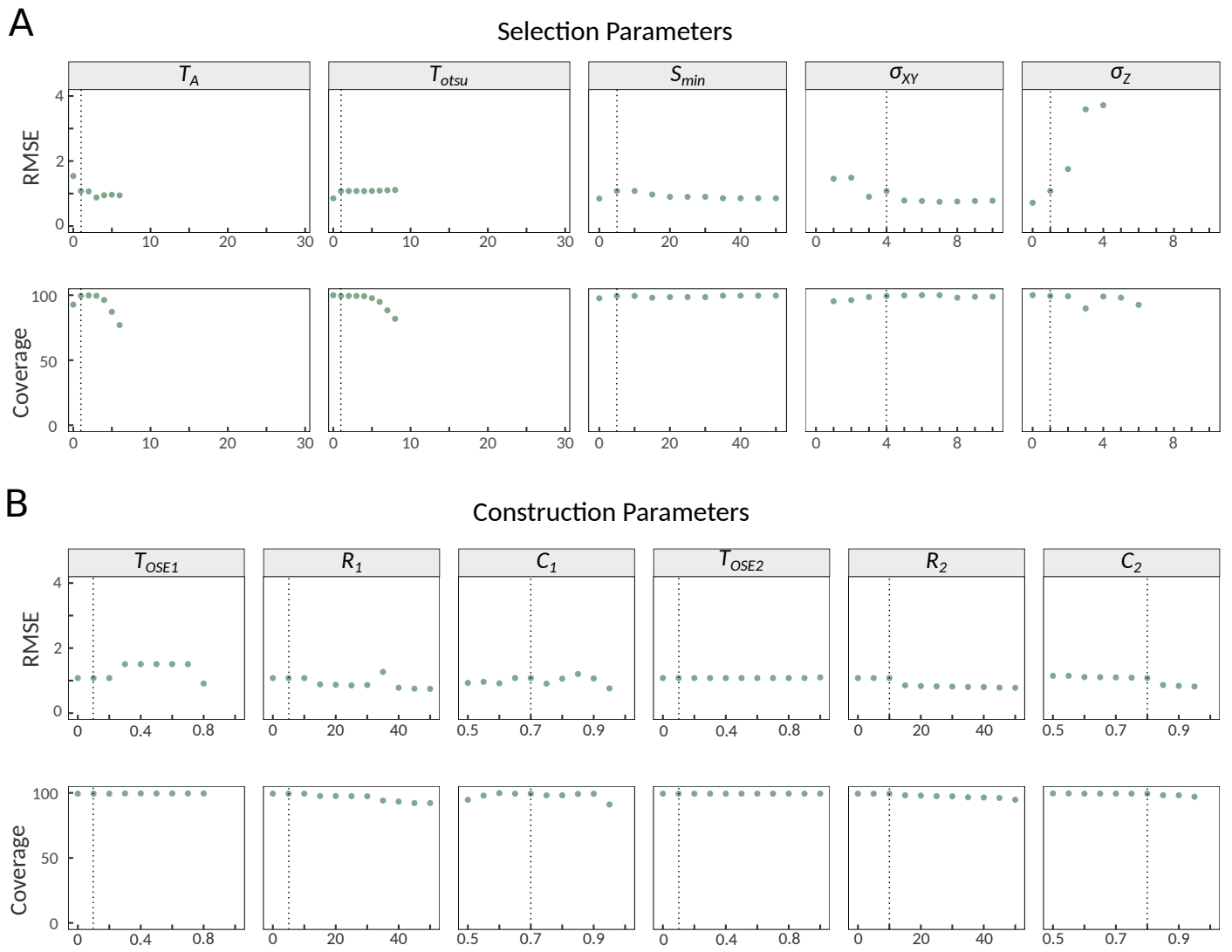


Figure S4. Sensitivity analysis of Zellige on the cochlear epithelium image. (A) Surface pixel selection parameters. **(B)** Surface assembly parameters. Reference values are indicated by the dashed line.

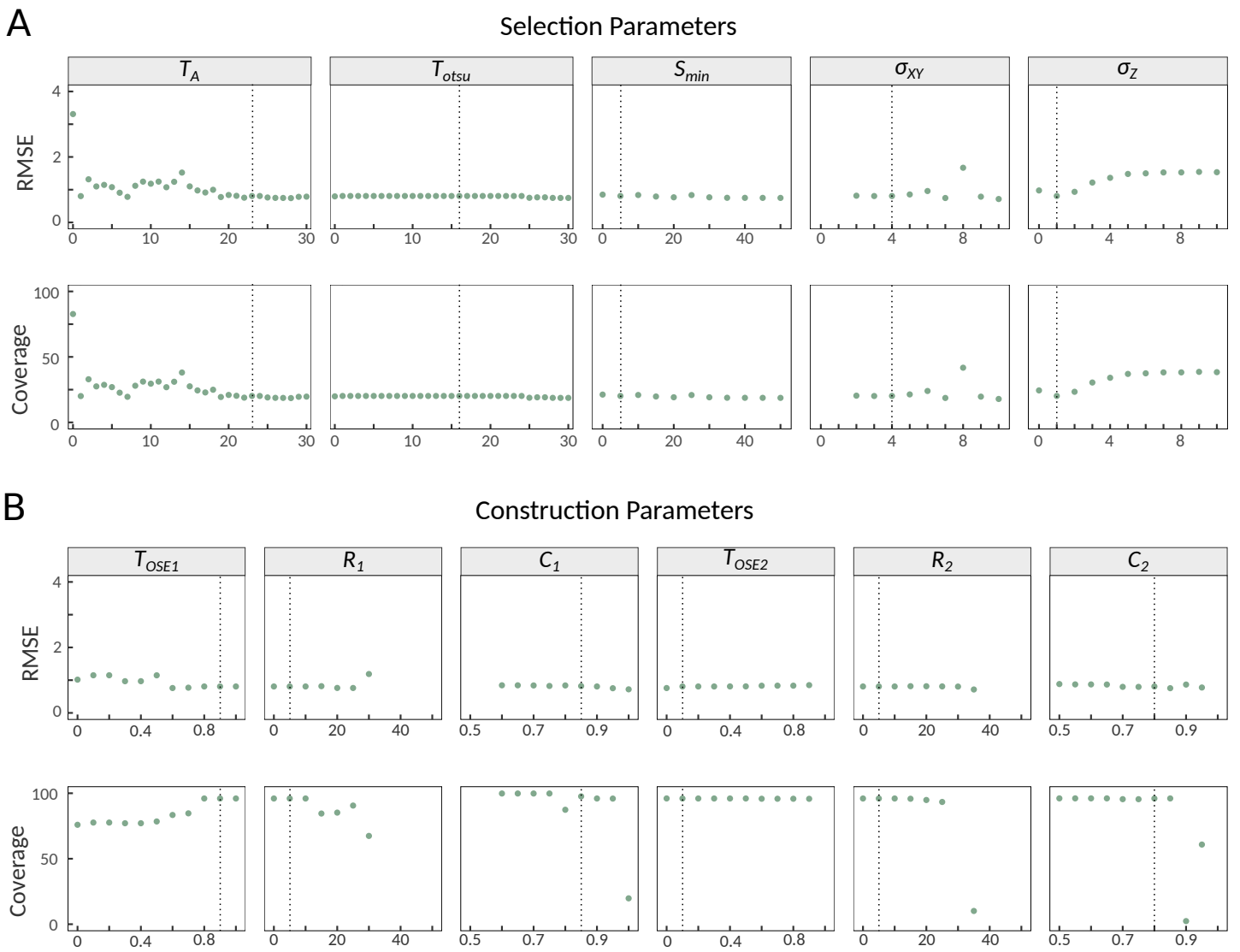


Figure S5. Sensitivity analysis of Zellige on the primary epithelium culture image. (A) Surface pixel selection parameters. **(B)** Surface assembly parameters. Reference values are indicated by the dashed line.

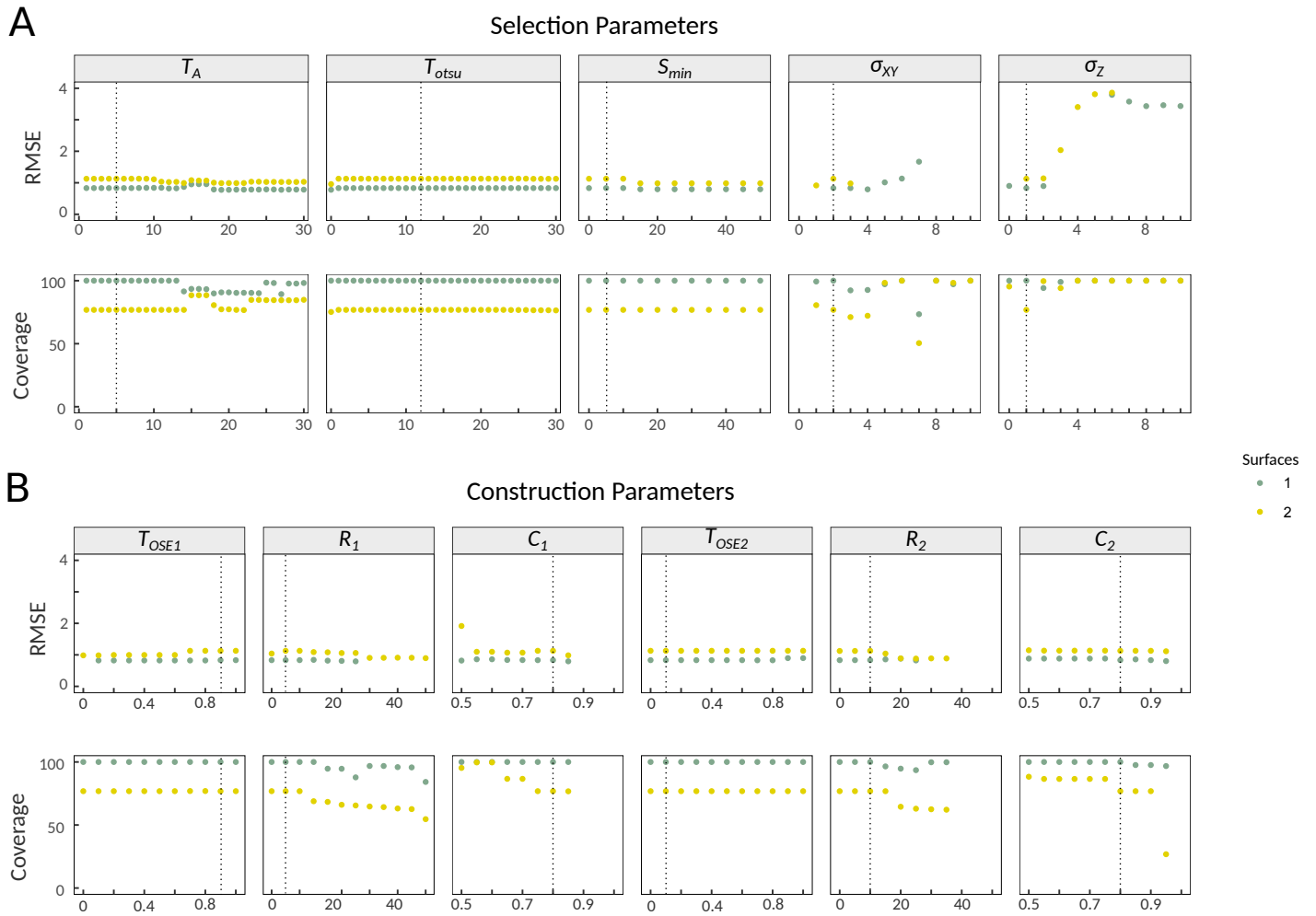


Figure S6. Sensitivity analysis of Zellige on the inner ear organoid image. (A) Surface pixel selection parameters. **(B)** Surface assembly parameters. Reference values are indicated by the dashed line.

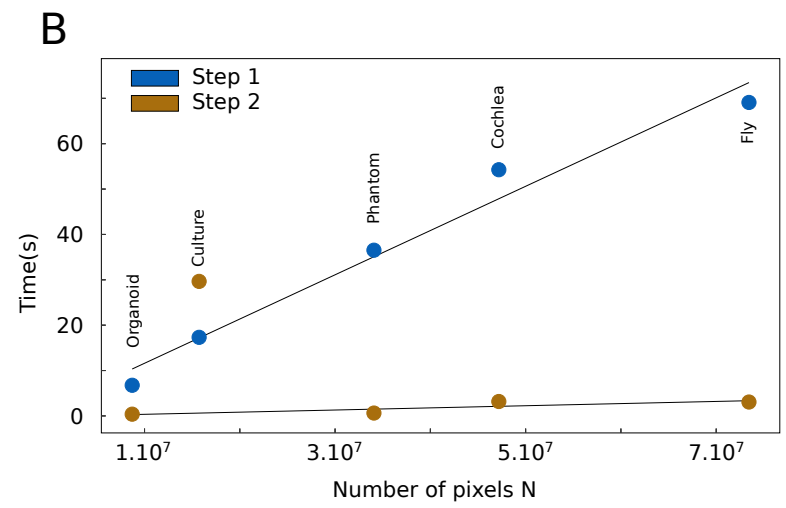
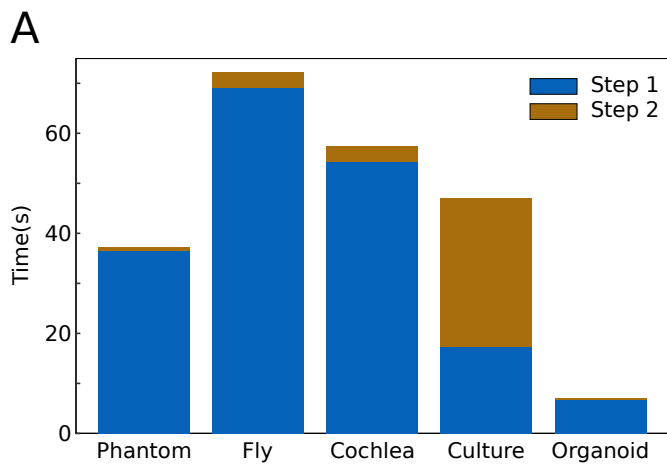


Figure S7. Computational time analysis of Zellige. (A) Computation times (step 1 in blue, step 2 in brown) for processing the various images tested on a PC notebook computer with (processor Intel Core i9 2,4 GHz with 32 Gb of Ram). Apart for the case of a highly rough surface (culture specimen) the computation time is largely dominated by the surface pixel selection step (step 1). **(B)** The same computation times are re-plotted as a function of image size N (number of pixels). Note the linear growth of the computational time of step 1 as a function of N , while that of step 2 shows much slower growth.

FIGURE S1

(A) The two main algorithmic steps of Zellige. Upper part: Surface pixel selection step (step 1). Lower part: Surface assembly step (step 2).

(B) Determination of the amplitude $A(p)$ of some local maximum p along the z axis, relative to its two closest local minima p_1 and p_2 .

(C,D) Connectivity rules used to connect putative surface pixels together for the construction of orthogonal surface elements (OSEs). These rules are based on a 6-connectivity relationship defined within each orthogonal (xz or yz) section as shown in (C). This relationship is extended to allow the presence of single straight gaps, while being constrained to forbid the occurrence of forking points. The allowed local neighborhood configurations along an OSE are illustrated in (D) in the case of a construction within xz sections. The OSEs are formally defined as the connected components of the graph G_{OSE} defined by these rules within each orthogonal section.

(E) Compatibility rules used in the surface assembly step, illustrated here in the case where OSEs have been constructed within xz sections, and assembly proceeds along the y axis. To validate the addition of a new OSE σ constructed within section $y+1$ (in blue) to the surface S under construction, whose intersection with section y is shown (surface line l_y , in green), two quantities are computed: the *overlap* $R(S,\sigma)$ is defined as the number of pixels of σ that share the x coordinate of some pixel of l_y . The *connectivity* $C(S,\sigma)$ is defined as the fraction of the overlapping pixels of σ that are 6-connected, in their respective yz section, to the corresponding point of l_y (according to the 6-connectivity relationship shown in C, middle panel). In the depicted example, $R(S,\sigma)=6$ and $C(S,\sigma)=6/6=1$. The OSE will be added to S if $R(S,\sigma) \geq R_0$ and $C(S,\sigma) \geq C_0$, where R_0 and C_0 are tunable thresholds that set the stringency of the matching condition.

FIGURE S2

Sensitivity analysis of Zellige on the phantom image. (A) Surface pixel selection parameters. (B) Surface assembly parameters. Reference values are indicated by the dashed line.

FIGURE S3

Sensitivity analysis of Zellige on the pupal fly image. (A) Surface pixel selection parameters. (B) Surface assembly parameters. Reference values are indicated by the dashed line.

FIGURE S4

Sensitivity analysis of Zellige on the cochlear epithelium image. (A) Surface pixel selection parameters. (B) Surface assembly parameters. Reference values are indicated by the dashed line.

FIGURE S5

Sensitivity analysis of Zellige on the primary epithelium culture image. (A) Surface pixel selection parameters. (B) Surface assembly parameters. Reference values are indicated by the dashed line.

FIGURE S6

Sensitivity analysis of Zellige on the inner ear organoid image. (A) Surface pixel selection parameters. (B) Surface assembly parameters. Reference values are indicated by the dashed line.

FIGURE S7

Computational time analysis of Zellige. (A) Computation times (step 1 in blue, step 2 in brown) for processing the various images tested on a PC notebook computer with (processor Intel Core i9 2,4 GHz with 32 Gb of Ram). Apart for the case of a highly rough surface (culture specimen) the computation time is largely dominated by the surface pixel selection step (step 1). (B) The same computation times are re-plotted as a function of image size N (number of pixels). Note the linear growth of the computational time of step 1 as a function of N , while that of step 2 shows much slower growth.