

## Supplement S2: Additional Details for Experimental Results

Using Euclidean distance as descriptor function. In Table 1, we provide the number of hits and success-rates for k-nearest neighbor classification based on persistence diagrams  $(d_P)$  and persistence-vectors  $(d_V)$  using Euclidean distance function as descriptor function. We note that the success-rates are comparable to (but slightly worse than) those obtained from the geodesic distance descriptor function.

Table 1: Leave-one-out cross validation for k-NN classification using Euclidean distance function as descriptor function

	# neurons classified correctly / success-rate for Dataset 1				
# nearest neighbors $k$	Persist-distance $d_P$	Persist-vec $d_V$			
1	$123 \ / \ 0.3555$	166 / 0.4798			
2	152 / 0.4393	200 / 0.5780			
3	164 / 0.4740	221 / 0.6387			
4	189 / 0.5462	238 / 0.6879			
5	203 / 0.5867	245 / 0.7081			

Comparison with L-Measure quantities. We also compare our persistence-based features with specially-designed summaries of neuron morphology contained in L-Measure [1]. This experiment is carried out for Dataset 1. We use only those L-Measure parameters reported in the meta-data associated to each neuron in NeuroMorpho.Org [2], which can be considered as common L-Measure quantities. These parameters are listed in Table 2 – We exclude the parameter "Soma surface" and "Number of stems" as the first one is not reported (i.e, 'N/A') for neurons in Dataset 1, and the second one is the same for all of them. For each individual parameter, we also list the success-rate of k-nearest neighbor classification when the distance between two neurons is computed based on this parameter alone (defined as the absolute difference between its values for the two neurons).

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Table 2: Leave-one-out cross validation using each parameter alone for Dataset1

	Results for different number of nearest neighbors					
L-Measure Parameters	1	2	3	4	5	
Number of Bifurcations	52 / 0.1503	86 / 0.2486	100 / 0.2890	125 / 0.3613	150 / 0.4335	
Number of Branches	45 / 0.1301	81 / 0.2341	107 / 0.3092	127 / 0.3671	150 / 0.4335	
Overall Width	19 / 0.0549	38 / 0.1098	54 / 0.1561	66 / 0.1908	80 / 0.2312	
Overall Height	52 / 0.1503	92 / 0.2659	105 / 0.3035	118 / 0.3410	133 / 0.3844	
Overall Depth	30 / 0.0867	53 / 0.1532	74 / 0.2139	93 / 0.2688	103 / 0.2977	
Average Diameter	23 / 0.0665	50 / 0.1445	64 / 0.1850	69 / 0.1994	78 / 0.2254	
Total Length	46 / 0.1329	77 / 0.2225	101 / 0.2919	120 / 0.3468	135 / 0.3902	
Total Surface	42 / 0.1214	71 / 0.2052	104 / 0.3006	131 / 0.3786	151 / 0.4364	
Total Volume	52 / 0.1503	85 / 0.2457	111 / 0.3208	126 / 0.3642	136 / 0.3931	
Max Euclidean Distance	51 / 0.1474	84 / 0.2428	117 / 0.3382	147 / 0.4249	168 / 0.4855	
Max Path Distance	41 / 0.1185	66 / 0.1908	78 / 0.2254	94 / 0.2717	111 / 0.3208	
Max Branch Order	26 / 0.0751	56 / 0.1618	66 / 0.1908	79 / 0.2283	86 / 0.2486	
Average Contraction	9 / 0.0260	11 / 0.0318	19 / 0.0549	33 / 0.0954	33 / 0.0954	
Total Fragmentation	46 / 0.1329	79 / 0.2283	102 / 0.2948	118 / 0.3410	129 / 0.3728	
Partition Asymmetry	13 / 0.0376	29 / 0.0838	45 / 0.1301	60 / 0.1734	58 / 0.1676	
Average Rall's Ratio	6 / 0.0173	24 / 0.0694	46 / 0.1329	52 / 0.1503	58 / 0.1676	
Avg. Bifurcation angle local	14 / 0.0405	29 / 0.0838	37 / 0.1069	46 / 0.1329	65 / 0.1879	
Avg. Bifurcation angle remote	32 / 0.0925	48 / 0.1387	72 / 0.2081	92 / 0.2659	104 / 0.3006	
Fractal Dimension	5 / 0.0145	18 / 0.0520	24 / 0.0694	33 / 0.0954	41 / 0.1185	

Next, we create a new feature-vector, denoted by  $L_T$ , for each neuron T from  $S = \mathsf{Dataset}$  1, where  $L_T$  simply consists of all the L-Measure quantities listed in Table 2. To compare two neurons under this feature vectorization, we use normalized  $L_2$ -norm between two vectors  $L_{T_1}$  and  $L_{T_2}$ . In particular, for the i-th parameter  $p_i$ , we first compute the mean  $\mu_i$  and standard deviation  $\sigma_i$  of it from its values over all neurons in S (Dataset 1); i.e,  $\mu_i = \frac{1}{|S|} \sum_{T \in S} L_T[i]$  and  $\sigma_i = \sqrt{\frac{\sum_{T \in S} (L_T[i] - \mu_i)^2}{|S|}}$ . Here,  $L_T[i]$  stands for the i-th entry of vector  $L_T$ , which is the value of this parameter  $p_i$  for neuron T. Let  $\ell$  denote the total number of L-Measure quantities we consider (i.e, the dimension of the feature vector  $L_T$ ). The normalized  $L_2$ -distance between two feature vectors  $L_{T_1}$  and  $L_{T_2}$  is defined as:

$$d_L(T_1, T_2) = \left[ \sum_{i=1}^{\ell} \left( \frac{L_{T_1}[i] - \mu_i}{\sigma_i} - \frac{L_{T_2}[i] - \mu_i}{\sigma_i} \right)^2 \right]^{1/2}.$$

In other words, this is the standard  $L_2$ -distance between  $L_{T_1}$  and  $L_{T_2}$  after each entry is normalized by its respective mean and variance.

The comparison of k-nearest neighbor classification accuracy is reported in Figure 7 (B) in the main text of the submission.

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## References

- [1] Scorcioni R, Polavaram S, Ascoli GA. L-Measure: A web-accessible tool for the analysis, comparison and search of digital reconstructions of neuronal morphologies. Nature Protocols. 2008;3(5):866–876.
- [2] Ascoli GA, Dohohue DE, Halavi M. NeuroMorpho.Org: A central resource for neuronal morphologies. J Neurosci. 2007;27(35):9247–51.

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