

Dear Mr. Negrello,

I am writing about the resubmission of the “Manifold-adaptive dimension estimation revisited” manuscript.

Thank you for the concise summary of the essential review-points and for the opportunity to improve and resubmit the manuscript.

We tried to extend and modify the text along the guidance of reviewers. Please see our point by point answer below.

Looking forward to your reply,

Sincerely,

Zsigmond Benko

Editor comments (Mario Negrello)

Please improve the problem statement, research question and rationale of the approach.

- *We added a new figure 1 to the revised manuscript to show the intuition behind the FSA intrinsic dimension estimator and also to demonstrate the limitation of the mean as global estimate.*
- *Also, we included some motivational description about the theory of nonlinear time series analysis in the Introduction and as a demonstration we present dimension estimation on the coupled systems the logistic maps .*

As per reviewer 2, please also consider in detail the consequences of hypercube corrections in the case of data with distributions other than the uniformly sampled hypercube.

- *We added an analysis on non-uniformly sampled or curved custom datasets (gaussian, hypersphere and Cauchy) as the Figure 7 of the revised manuscript. This analysis shows some limitations of our approach: the correction may lead to overestimation of the intrinsic dimension if the manifold is curved or extremely non-uniformly sampled.*

As reviewer 2 suggests, please consider making the code available, as it is best practice for methodological papers as yours.

- *We made the code available on github at the https://github.com/phrenico/cmfsapy/tree/main/examples/article_results/ url.*
- *We created an installable python package and uploaded to the Python Package Index (PyPI).*

Please also adjust the structure of the paper to conform to PeerJ guidelines, according to reviewer 1 as well.

We restructured the paper according to the guidelines:

- *In the end of Introduction we phrase the aims of the article in a more structured*

way

- We moved the Methods after the introduction sections
- Added the Conclusion section

Dear Reviewer,

I really appreciate your work on reading and commenting on the “Manifold-adaptive dimension estimation revisited” manuscript. I found your suggestions especially helpful on the structure of the paper, as well as the comments and question shed light on several inconsistencies in the notation and on not clear wordings.

We tried to restructure the manuscript to conform with journal-specific guidelines, to clarify the notation, to rephrase the ambiguous sentences and to improve the quality of figure captions.

I send you the point-by-point answer to your comments below.

Best regards,
Zsigmond Benko

Reviewer 1 (Anonymous)

Basic reporting

The language is generally clear, but it can be improved in certain sections. The literature is well referenced. The structure is not conforming to PeerJ Computer Science standard (namely, the Methods section should be placed right after the Introduction, not after the Discussion). The figures are high quality, but adding more details in the corresponding captions would facilitate their comprehension.

Experimental design

The article tackles a critical problem in the computer science field - dimensionality estimation. The research question, however, should be better stated in the introduction. Specifically, authors should clearly state the rationale and the aim of their study. The methods should be moved after the introduction and before the results so as to facilitate the reader following the flow of the article.

Validity of the findings

The proposed approach solves certain limitations of the algorithm that is based on. The authors performed an extensive comparison of their approach with other state-of-the art algorithms on various synthetic datasets. Perhaps, an additional comparison of the proposed approach with such algorithms on neural data might be ideal. Conclusions are missing.

Comments for the Author

The paper sets to revisit a dimensionality estimation algorithm, the manifold adaptive

Farahmand-Szepesva'ri-Audibert (or FSA). The authors first computed the local probability density function following the original FSA pipeline and then e the median of such pdf to obtain the global estimate of the dimensionality. They further corrected for finite sample effect implementing a correction formula and finally compared the performances of their algorithm with those of the original FSA as well as other state-of-the-art techniques. The proposed approach outperforms the original FSA and perform similarly to other methods when applied to synthetic datasets. When applied to neural signals recorded during epileptic seizures, the authors hypothesize that low-dimensional brain regions might be potential sources for the seizure onset.

The overall structure of the paper is ok to follow. However, certain parts of the manuscript can be improved and some details need to be added. Following are some specific comments.

1. Line 96. I suggest you provide more justification for your study. What is the rationale of your approach? How do you expect your result to differ from the original FSA algorithm? Also, could you be clearer when you say 'we correct the underestimation effect by an exponential formula'?

- I extended the Introduction by 2 motivational examples and inserted an additional figure about the dimension estimation procedure.*
- This figure (the new Figure 1) also shows the empirical observation that the median of local estimates is more robust estimator of the intrinsic dimension than the mean.*
- I added the paragraph to make the case for the study at line 118:*

“We showed in the previous two examples that the median of local FSA estimates was a more robust estimator of the intrinsic dimension than the mean but the generality of this finding is yet to be explored by more rigorous means. Additionally, in these cases the data were abundant, and the edge effect was softened by periodic boundary, but data can be scarce and the manifold may have finite size causing systematic errors in the estimates of intrinsic dimension.”

- Also, I changed the last paragraph to make the sentence with the “exponential formula” clearer at line 132:*

“We present the new corrected median FSA (cmFSA) method to alleviate the underestimation due to finite sample and edge effects. We achieve this by applying a heuristic exponential correction-formula applied on the mFSA estimate and we test the new algorithm on benchmark datasets.”

2. Line 98, end of introduction. Could you please add some description of your following section in a clearer way?

- I included an enumeration containing the main contributions of the paper, starting form line 123.*
- I added a paragraph about the organization of the paper at the end of the Introduction section at line 137:*

*“The paper is organised as follows.
In the Methods section, we present the steps of FSA, mFSA and cmFSA*

algorithms, then we describe the simulation of the hypercube datasets and we show the specific calibration procedure used in the cmFSA method. After these, we turn to benchmark datasets. We refer to data generation scripts and display the evaluation procedure. This section ends with a description of Local Field Potential measurements and the analysis workflow. In the Results section, we lay out the theoretical results about the FSA estimator first, then we validate them against simple simulations as second. Third, we compare our algorithms on benchmark datasets against standard methods. Fourth, we apply the mFSA algorithm on Local Field Potential measurements. These parts are followed by the Discussion and Conclusion sections.”

3. Authors should also compare their approach to the original FSA (or to some other methods) on the neural dataset and not the synthetic ones only.

- *I inserted a new subplot into the corresponding figure (Figure 9 B in the revised manuscript), which shows a comparison of original FSA and mFSA estimates plotted against each other for different neighborhood sizes.*

4. The method section should be moved right after the introduction. This would allow to describe the proposed approach before showing the corresponding results. Moreover, some results are already described in this section (e.g., lines 252, 256, 274). Those sentences should be removed and included in the results section only. Also, please put the figures closer to the corresponding location in the main text where they are referred to.

- *I moved the Methods section after the Introduction.*
- *Also, I added two subsections into the Methods about the original and proposed variants of the FSA algorithm with the steps of the algorithms. (“FSA and mFSA algorithm”, “cmFSA algorithm” subsections)*
- *I removed lines 252, 256, 274 from the Methods section.*
- *I altered the position of figures in the LaTeX code, which hopefully helps to bring them closer to the corresponding locations in the text*

5. Authors should add a conclusion section.

- *I added the Conclusion section.*

6. Line 167, cmFSA acronym should be defined before use.

- *In the revised text, I define the mFSA and cmFSA acronyms at the end of Introduction in the main contributions part.*

7. Line 244, authors should justify why they chose to test those three specific values of k .

- *I added few sentences about this specific choice at line 179: “We selected these specific neighborhoods because of didactic purposes: the $k = 1$ neighborhood is the smallest one, the $k = 50$ is a bigger neighborhood, which is still much smaller than the sample size, so the estimates are not affected by the finite sample effect. The $k = 11$ neighborhood represents a transition between the two “extremes”, the specific value is an arbitrary choice giving pleasing visuals suggesting the gradual change in the shape of the curve as a function of the k parameter.”*

8. There are some inconsistencies related to the use of the notation for the true and the predicted dimensionality. According to line 255, D indicates the true dimensionality and

d the predicted dimensionality. However, in line 270 you use d to indicate the true dimensionality and \hat{d} for the predicted one. Choose one notation and stick with it.

- I corrected the inconsistency by
 - using D for the true dimension and
 - small d for the global estimated value
 - also I introduced δ for the local dimension values

9. The captions of each figure should be more detailed. Specifically, they should briefly describe the take-home message of the figure (one or two sentences are enough).

- I added take-home message to each figure-caption

10. Figure 1: it is not clear to the reviewer how the histogram was obtained. Didn't you test only one realization in this case (line 242)?

Yes it was one realization of random-uniform hypercube dataset with $n=10\,000$ sample points. The figure shows the probability density of the local estimates, which is computed for each sample point. The histogram was obtained from the local estimates ($n=10\,000$).

I modified the title of the figure (Figure 2 in the revised manuscript) to contain the "local" word, to make it more clear that the probability density of the local dimension values are depicted in the figure.

Also I changed the notation, because the local values were also denoted by " d ", I assigned the δ symbol to local dimension values and modified the x-axis of the subplots accordingly.

11. Table I: what are $cmFSA_{fr}$ and $M_{DANCO_{fr}}$?

I used $cmFSA$ and $DANCo$ in two modes: in integer mode and in fractal mode. In the former, the global dimension values were rounded to the nearest integer value, but in the latter case they were left alone as real numbers. I applied the following changes to the revised text:

- I added this detail to the Methods section at line 223:
"We used $cmFSA$ in two modes, in integer and in fractal mode. In the former the global estimates are rounded to the nearest integer value, while in the latter case the estimates can take on real values."

and a bit later at line 229:

"In the case of $DANCo$, we also investigated the results for integer and for fractal mode just as for the $cmFSA$ algorithm."

- I added the " $cmFSA$ and $DANCo$ was applied in integer and in fractal modes." sentence to the caption of table I.

Dear Mr. Allegra,

Thank you for your work in scrutinizing and commenting on the manuscript titled "Manifold-adaptive dimension estimation revisited". Your comments were invaluable: they led several to additional results and improved the overall quality of the article.

I tried to improve the research motivation part by adding an new figure to the manuscript, changed the notation to improve the clarity of the derivations and included additional results on the standard error of the median supported by derivations packed into the SI, also I added

several subplots to the figures to make them more expressive.

Please, see our point-by-point reply to your questions and comments below.

Best regards,
Zsigmond Benko

Reviewer 2 (Michele Allegra)

Basic reporting

The manuscript is sound and well written. References are generally exhaustive. The methodology is clearly explained.

Experimental design

The propose method seems to be competitive with state-of-art methods, and I believe it offers some advantages with respect to some of issued of ID estimators, in particular boundary effects, and variations of the density of points in the data.

I think the manuscript is a fair contribution to the field of ID estimation, and it can be of interest to researchers in this area, and more in general to researchers needing accurate ID estimation as part of their data analysis pipelines.

Validity of the findings

Major comments:

1) In my opinion, the main problem with the boundary-effect correction is that it is optimized for uniformly-sampled hypercubes, and may lead to overestimation of the ID in cases when the data are not uniforly sampled. This is clearly visible form table I: while the estimation is nearly perfect for uniformly sampled data on linear subspaces [M2,M9,M10a-c], or generally uniformly sampled data on locally at spaces [M5,M7,M13], it yields an overestimation in the case of non-uniformities, such as he Gaussian case [M12], the non-linear manifold case [M6], or the sphere [M1]. The overestimation may be even more sever for non-uniform samplings with heavy-tailed distributions, such as the Cauchy distribution used in Facco et al. 2015. The authors should extensively comment on this point.

- To investigate the non-uniform sampling case, I did an analysis on uniform, gaussian, cauchy and hypersphere datasets as in the Figure 2 of Facco 2017. (inserted as the new figure 7.)
- Added the 2NN estimator of Facco to the simulated benchmarks
- extended the discussion section supposedly along the guidelines given by the reviewer:

line 424:

“One can try to address the effect of curvature and nonuniform density with the choice of minimal neighborhood size ($k = 1$), thus the estimation error is minimal (Facco 2017). We investigated cases when the flatness and uniformity assumptions is violated on curved and unevenly sampled manifolds as in Facco 2017 and found that the estimation errors can be large both for mFSA and cmFSA. We investigated the non-uniform sampling with Gaussian and Cauchy datasets ($k = 5$). For the Gaussian dataset cmFSA moderately overestimated the values. For the Cauchy dataset the overestimation of cmFSA is very severe: for less than 500 points, the estimation error and also the standard deviation seems to be unbounded. On the curved hypersphere data cmFSA

also produced moderate overestimation. These datasets are quite challenging, and the 2NN method of Facco 2017, which uses minimal neighborhood information, presents more exact results on these. The simplicity of the correction in cmFSA, more specifically that the calibration is based on uniformly sampled hypercube datasets makes it vulnerable to non-uniform density and curvature.”

and later around line 450:

“More specifically in the cases of M_1 , M_6 , M_{12} cmFSA almost never hits the true intrinsic dimension value, where M_1 is a 10-dimensional sphere, M_6 is a 6-dimensional manifold embedded in 36 dimensions and M_{12} is a 20-dimensional multivariate Gaussian. In the first case the manifold is curved, in the second it is embedded in high dimensional ambient space and in the third one it is non-uniformly sampled. DANCo was robust against the curvature and the non-uniform sampling, but also exhibited vulnerability to high ambient space data M_6 . For this dataset the 2NN method performed the best.”

Facco, E., d’Errico, M., Rodriguez, A. et al. Estimating the intrinsic dimension of datasets by a minimal neighborhood information. Sci Rep7, 12140 (2017). <https://doi.org/10.1038/s41598-017-11873-y>

2) Since this is a methodological work, I would recommend that the authors make publicly available the code implementing cmFSA.

- We made the code available at the <https://github.com/phrenico/cmfsapy/> URL and
- we also uploaded an installable python package to the Python Package Index.

3) It is not clear how the different sample sizes were included in the calibration of the correction term. It seems that the calibration term used to infer the ID of the datasets M_1 - M_{13} was inferred from the $n = 2500$ hypercubes. Is one going to use the same term with datasets of different n ? It seems that one should rather use a term calibrated on that specific n . The authors should comment on this point. Furthermore, why was $k = 5$ used for calibration, instead of $k = 1$ used in subsequent analyses?

Yes, the calibration procedure has to be carried out for each specific n . In the subsequent analysis. We corrected the manuscript to make the description more clear on this part, I inserted that the coefficients are sample size dependent into the results. Also I included additional descriptions of the estimation algorithm into the methods section, where I explicitly state, that the correction model is for a specific sample sizes approximately at line 158 of the revised manuscript:

“Fit a correction-model with the the given sample size n on uniform random hypercube calibration datasets consisting of various intrinsic dimension values, many instances each (at least $N=15$ realizations).”

I used $k=5$ neighborhood size on the benchmarks, because bigger neighborhoods result in smaller variance in the estimates. It comes with the price of higher bias, but this bias is corrigated by the correction formula. Additionally in real-world datasets the effect of noise can be ameliorated by bigger neighborhood choice, presumably the same effect can be seen on the Figure 9 B of the revised dataset, where the dimension estimates of the LFP channels are depicted in the function of neighborhood size. Here the mFSA estimates are higher for smaller neighborhood sizes, a possible explanation is the noise on the data.

Minor points:

- The Authors may better stress the fact that their median-based procedure is independent of k , and thus allows selecting a minimal neighborhood size ($k = 1$). In this case, the used statistics is essentially equivalent to the

one used by Facco et al., 2017 - even though the estimation procedure is slightly different. As in Facco et al., using a minimal size neighborhood can make the method very robust to density variations and curvature.

I inserted a figure and 2 sentences points into the main text to emphasize the relevance of this finding:

1. in the Introduction section: I inserted the new Figure 1. C D, which shows that the sample median is a good estimator even in small neighborhood sizes
2. in the discussion section I inserted at line 413:
"This property holds even for the minimal $k = 1$ neighborhood size, where the previously proposed mean is infinite. The use of minimal neighborhood may be relevant, because it ameliorates the effect of curvature and density inequalities"
3. in the conclusion section at line 478:
"We derived the probability density function of local dimension estimates for uniform data density and proved that the median is an unbiased estimator of the global intrinsic dimension, even at small neighborhoods."

- The simplicity of the proposed statistic makes it suitable to be embedded within mixture-based approaches to provide better ID estimates whe the ID is varying in the data set (Haro, G., Randall, G. & Sapiro, G. Translated poisson mixture model for stratification learning. Int. J. Comput.Vis. 80, 358(cid:21)374 (2008); Allegra M, Facco E, Denti F, Laio A, Mira A (2020) Data segmentation based on the local intrinsic dimension. Sci Rep 10(1):16449).

In the Discussion at line 407 I added:

"However these results were derived for the simplest uniform euclidean manifold with single global intrinsic dimension, they form a base for application in more complex cases.

For example the pdf of the local statistic make possible to apply the FSA estimator within mixture-based approaches, this would provide better ID estimates when the ID is varying in the data set (Haro2008, Allegra2020)."

- The Authors may better clarify Eqs. (1-2). In Eqs (1-2), k is used to indicate both a variable quantity and a fixed quantity. In eq. (1), k is a variable quantity, like R [notice that Eq.(1) now uses both R and R_k , inconsistently]. In eq. (2), k is a fixed value, like r_k and r_{2k} . Also, the quantities in Eq. (1) should be better defined. I would recommend something like:

A usually basic assumption of kNN ID estimators is that the fraction of points f in a spherical neighborhood centered at x is approximately determined by the intrinsic dimensionality (D) and radius(R) times a locally almost constant mostly density-dependent factor($\eta(x, R)$):

$$f/n = \eta(x, R)RD$$

[...] If R_k is the distance at which the k -th neighbor is found, from Eq. (1) one can take the logarithm..."

We modified equation 1 and 2 (eq. 2 in revised manuscript) supposedly according to the guidelines. We also modified the definitions and the description for the derivation of equation 3.

starting from line 70:

“A usually basic assumption of kNN ID estimators is that the fraction of points f in a spherical neighborhood is approximately determined by the intrinsic dimensionality (D) and radius (R) times a -- locally almost constant -- mostly density-dependent factor ($\eta(x, R)$, Eq.2).

$$f \approx \eta(x, R) * R^D$$

where f is the fraction of samples in a neighborhood.”

after line 97:

“We derive the FSA estimator from Eq. 2. Let \mathcal{M} be a D dimensional manifold and let's have a sample $\{x_i\}$ where $i \in \{1, 2, \dots, n\}$ with n size sampled from \mathcal{M} .

We take two neighborhoods around a sample point, thereby we fix $f = k/n$ and if R_k^i is the distance at which the k -th neighbor is found around x_i , then we can take the logarithm of both sides:

$$\ln\left(\frac{k}{n}\right) \approx \ln \eta + D \ln R_k^i$$

$$\ln\left(\frac{2k}{n}\right) \approx \ln \eta' + D \ln R_{2k}^i$$

If η is slowly varying and ΔR is small, we can take $\eta = \eta'$ as a constant.

Thus, by subtracting the two equations from each other we get rid of the local density dependence:

$$\ln(2) \approx D \ln\left(\frac{R_{2k}^i}{R_k^i}\right)$$

• In Eq. (5), the Authors may better clarify what $p(r|k, K-1, D)$ is: something like the probability that the normalized distance of the k -th neighbor among K neighbors is r if the intrinsic dimension is D .

I inserted the sentence at line 283:

“Here $p(r|k, K-1, D)\Delta r$ describes the probability that the k -th neighbor can be found on a thin shell at the normalized distance r among the $K-1$ neighbors if the intrinsic dimension is D (see SI\,A.\,1 for a derivation).”

• Thus, we can compute the pdf of the estimated values as plugging in $K = 2k$ into Eq. 5 followed by change of variables(p. 4). This sentence might be more clearly rephrased, e.g., Combining (5) and (6), one can obtain the pdf of the FSA estimator

I changed the text according to the suggestion at line 291:

“Combining Eq.13 and Eq.14 one can obtain the pdf of the FSA estimator:”

• In theorem 1, the Authors may mention that the substitution $a = 2-D/dk$ is monotonic, which justifies the invariance of the median.

I changed the text to mention the monotonicity of the mapping at line 297:

“and α is a monotonic function of δ , therefore the median in δ_k can be computed by the inverse mapping.”

- *This means that the median of the FSA estimator is equal to the intrinsic dimension independent of neighborhood size. Again, this fact should be stressed because it allows using small k , which cannot be done in standard FSA: indeed, for small k , as evident from fig. 1, the mean and mode produce severe underestimates.*

I modified the sentence at line 299:

*“This means that the median of the local FSA estimator is equal to the intrinsic dimension independent of neighborhood size, **even for the minimal neighborhood**, if the locally uniform point density assumption holds.”*

- *In Fig. 2, the Authors may add a third panel showing on a simple plot the standard error of the median as a function of $\log(n)$, for different values of D different curves for different values of D .*
- *I added a third C and a fourth D panel to figure 3, showing the standard error of the estimates in the function of $\log(n)$ and also in the function of neighborhood size.*
- *The analysis led to the result that the standard error is proportional to D/\sqrt{kn} approximately (eq.26 in revised manuscript and SI section D).*
- *I also derive this sample-size and neighborhood dependence by using the Laplace approximation for the median and Stirling approximation for the Euler-beta function (SI section D).*
- *I would put a derivation of Eq. (17) in the SI. (the rationale of the binomial is nearly obvious, but a full explanation may help the reader).*
- *We included a general derivation for the pdf of the sample median in the SI section C.*
- *Are periodic boundary conditions used in Figure 4, as the main text indicates? This should be clarified also in the caption of Fig. 4, to stress the difference with Fig. 3, which is not using PBC.*

Yes, we used periodic boundary conditions for the old figure 4.

In the revised manuscript Figure 4, Figure 5 and Figure 6 are involved, we modified the captions to contain the boundary conditions.

- *In eqs. (21)-(22) it would be better to bring in some notational clarity. What are d , D , \hat{d} ? Note that D was always used as the true value of intrinsic dimension.*

I changed the notation, introduced δ for local id estimates, d stands for global estimates, and big D is used for the true dimension value in the revised text.

- How is the error in Fig. 6 defined? It is stated that the error rate is the fraction of cases, when the estimator did not and (missed) the true dimensionality. What does this mean exactly? That $|D_j - d_{ij}| > 1$?

I inserted the definition of error rate into the revised manuscript, this metric is defined only for integer mode estimators (DANCo, cmFSA in integer mode) (line 232):

“Also, we used the error rate -- the fraction of cases, when the estimator did not find (missed) the true dimensionality -- as an alternative metric. We used this metric to compare the performance of DANCo and cmFSA in integer mode, we simply counted the cases, when the estimator missed the true dimension value:

$$H_j = \frac{1}{N} \sum_{i=1}^N I(D_j \neq d_{ij})$$

where H_j is the error rate for a manifold computed from N realizations and $I = 1$ if $D_j \neq d_{ij}$ is the indicator function for the error.

We computed the mean error rate H by averaging the manifold specific values.”

- In fig. 7, what are 1-8 on the x axis? Is it simply the electrode number? To what areas do the grid recordings Gr-A ... Gr-F correspond? The Authors should specify it in Methods, or at least provide a reference.

We improved the old figure 7 (became Figure 9 in the revised text).

In Fig 9 A we included the layout of electrode grid on the brain surface and the C D E subplots has axis labels now, also we modified the descriptions in the Methods at line 236:

“We used data of intracranial field potentials from two subdural grids positioned -- parietofrontally (6*8 channels, Gr A-F and 1-8) and frontobasally (2*8 channels, Fb A-B and 1-8) -- on the brain surface and from three strips located on the right temporal cortex (8 channels, JT 1-8), close to the hippocampal formation and two interhemispheric strips, located within the fissura longitudinalis, close to the left and right gyrus cinguli (8 channels BIH 1-8 and 8 channels JIH 1-8) as part of presurgical protocol for a subject with drug resistant epilepsy (Fig. 9 A).”

- Why was $k = 10$ used in the analysis of electrode data? If results change a lot between $k = 1$ and $k = 10$, it may be because data were not optimally subsampled.

In Figure 9 the new B subplot shows the neighborhood-dependence of the estimates. From this it can be seen, that $k > 5$ neighborhood is required to get above the noise level to obtain stable estimates as an alternative to further subsampling.

- In Fig. S2, I would stress that panel c shows that the error distribution after correction is approximately Gaussian.

We added panels E and F to Sfig 2 to address this caveat, E shows that the shape of the error is indeed Gaussian-like. Panel F shows that it can not be rejected that the

error-samples are generated from Gaussian distributions.

We observed a diagonal gradient of intrinsic dimensions on the cortical grid (Gr)(p. 7). It is difficult to interpret a diagonal gradient (as opposed to a vertical gradient representing cortical hierarchy).

We rephrased this part of the results section (line 389):

“We found several characteristic differences in the dimension patterns between normal and control conditions. In interictal periods (Fig. 9 C), we found the lowest average dimension value at the FbB2 position on the froto-basal grid. Also, we observed gradually increasing intrinsic dimensions on the cortical grid (Gr) between the F1 and D6 channels. In contrast, we observed the lowest dimension values at the right interhemispherical strip (JIH 1-2) and on the temporo-basal electrode strip (JT 3-5) close to the hippocampus, and the gradient on the cortical grid altered during seizures (Fig. 9 D). Comparing the dimensions between seizure and control periods, majority of the channels showed lower dimensions during seizures. This decrease was most pronounced close to the hippocampal region (strip JT) and the parietal region mapped by the main electrode grid (GrA-C). Curiously, the intrinsic dimensionality became higher at some frontal (GrE1-F2) and fronto-basal (FbA1-B3) recording sites during seizure (Fig. 9 A and E).”