**Reviewer 1**

The authors propose a new method to recognize regularity patterns in point

clouds by assigning to each point a quantitative index that represents the degree

of disorder of that point’s neighborhood. Given a point cloud, the core idea is

to select two close points and compare their neighborhoods by computing an

optimal matching between the points of the two neighborhoods and averaging

the matching distances. The Index of Disorder (IoD) assigned to each unit of the

point cloud is the average of the aforementioned quantity over all the pairings

of the point itself and a point in its neighborhood.

The proposed method is applied to simulated data and to different real-

world scenarios: patterns of reforestation areas, organization of an orchard and

ordering of the buildings in a city neighborhood.

The work is well written, and all the steps of the algorithms are clearly

explained. The simulated examples and the real-world cases are meaningful

and the results of the analysis are interesting.

However, more formal justifications of some steps is lacking. A more detailed

analysis of the model parameters or the possibility to automatically optimize

them using, for example, information theoretic criteria, is not properly treated.

I think using ITC/AIC goes beyond the scope of what we’re doing here…. Also to my understanding ITC is about selecting the optimal model, not optimizing a model. So I’m not sure how to handle this. I need to research ITC more

Moreover, the literature review does not stress enough the importance and the

concrete purpose of the proposed solution.

I have added additional text justifying the novelty and purpose of the IoD to the end of the introduction.

The following are some specific comments for the authors to improve the

manuscript:

• the possibility of using optimal transport (OT) algorithms for matching

the sub point clouds of the two neighborhoods is not mentioned, though

some OT algorithms would remove the problem of non matching points by

finding a hybrid matching. Setting the problem of neighborhoods match-

ing in the OT framework could make the solution more theoretically jus-

tified.

The problem of optimally matching neighborhoods is an interesting one, and there are many possible solutions. The Hungarian method is a classic solution to the assignment problem which is why we chose to use it. This paper is meant to demonstrate one possible implementation of the IoD; though there may be more optimal implementations, we feel testing them goes beyond the scope of we what are intending to demonstrate. However, we have added a note in section 2.1.1 (Point Pair Assignment) about the possibility of using other solutions to the assignment problem.

Should we talk about OT algorithms?...

• it is not clear how to select a good IoD threshold. A more formal definition

of the meaning of a threshold on the IoD would improve the quality of the

manuscript and the practical applicability of the methodology proposed.

I have added an explanation of the threshold to the end of the first paragraph of section 2.3 (Applied Evaluations)

• the advantages of a quantitative index of disorder instead of a pattern

detection algorithm are not clearly explained and underlined. In the three

real-world examples considered in the manuscript, a threshold is applied

to the IoD to obtain an ordered/non-ordered classification of the points:

what is the advantage of the proposed algorithm with respect to classical

pattern-detection algorithms such as those described in the introduction?

I have added additional details in the conclusions section

• comparison with similar algorithms on the same three use cases is lacking.

In the real-world examples, where the IoD is used to detect patterns,

comparison with classical pattern-detection algorithms should be made.

The IoD provides a quantitative measure of disorder at each point within a set of points. Thus, it can not be directly compared to the classical pattern detection algorithms described in the paper, as these algorithms delineate repeating motifs rather than quantify disorder at each coordinate location. These algorithms are not suitable for thresholding ordered vs disordered points. The IoD also cannot be compared to the raster-based operators described in the passage, as the IoD evaluates disorder in point sets, not raster data.

The IoD could theoretically be compared to the algorithm described in Antuono et al. (2014). However, that algorithm was designed for use in simulated fluid particle systems and makes assumptions of an underlying grid structure. While such a comparison could be interesting, it is probably beyond the scope of this paper.

• the meaning of the comment in the sentence at lines 368 to 370 about the

backward use of the IoD is not clear. A more detailed explanation or an

example may help clarify it.

I have provided additional clarification on this in the Conclusions section

• The authors should check carefully the English throughout the manuscript,

here are some typos:

\* Line 21 “Different set of methods” → “Different sets of methods”

\* Line 92: “such that that average” → “such that average”

\* Line 138: “... when assigning a neighborhood with few points to

another with many points what could lead to a small IoD” → “... as-

signing a neighborhood with few points to another with many points,

that could lead to a small IoD”

\* Line 369: “then then an optimization” → “then an optimization”

\* Caption of Figure 2: “The process then repeated” → “The process

is then repeated”

I have addressed these specific typos

**Reviewer 2**

This article presents a metric (IoD - Index of Disorder) to find patterns in sets of points, i.e., ordered points and disordered points. The metric consists of quantifying the distance (or similarity) between two subsets of points (two neighborhoods), with or without a previous alignment of the points in the two neighborhoods. The authors argue that there are cases where alignment improves results and in others it worsens. The experiments use datasets generated by the authors and three real datasets. The three case studies are interesting and the proposed method has good results in two of them.

The authors make simple choices when applying the IoD metric, but they seem to have strong implications in the results. For example, the authors decide 'to punish unpaired points if and only if they are within the convex-hull of the subset of points that have an assignment'. This choice is well suited when the contour enclosing the points to be analyzed is approximately convex (a rectangle or a circle, as in the proposed examples), but it may not be the case when that contour is irregular, e.g., if there are large convexities or empty regions (holes). It also does not solve issues like scaling as referred to in the article. In my opinion, the authors should work on these issues to make the overall solution more robust and to achieve good results in a wider range of use cases.

Issues with pattern scaling may be obviated by the application of Iterative Closest Point (or similar) reorientation, which can include scaling. The concerns raised regarding the deficiencies of using the convex hull to make a decision on whether to punish unpaired points are valid, and the text has been updated to reflect tshis in section 2.1.4. Future work should include investigation on how to handle irregularly contoured patterns.

+ + + Detailed comments

+ L81..84: the second coordinate transformation refers to the alignment of two subsets (neighbourhoods)? The meaning of the sentence "The IoD sub-score is not the IoD itself, but rather an intermediate parameter used …" is difficult to understand. Please, explain it better, including the meaning of the intermediate parameter.

This explanation has been improved (2.1).

+ L115..117: In my opinion, Figure 4 does not illustrates well issues such as translation, rotation, skewing, etc. of two point sets, but these are well-known concepts in point set registration algorithms and so it is not necessary to illustrate them. Suggestion: remove the cross-reference to the figure.

Maybe? I think it’s fine but we could remove it

+ L166..170. There are choices in 'The values adopted for…' hard to understand, e.g., 1) what is the meaning of 'punishment of points outside of the convex hull set to false'?

The parameterization was presented poorly and has been updated to be more understandable. Additionally, an explanation of sigmoidal function parameters was added to section 2.1.1 (Point Pair Assignment) as this was not explained anywhere in the text other than a figure caption.

+ L196..198, L208..212 and L228..230 are basically the same (repeated). This is a comment on aesthetic only.

This is true; I have elected to retain this as it may help orient readers to our methods who may not be reading the paper in its entirety or in order

+ L281. Why, what does it means and how do you ascertain that 'points become disordered'?

Because the optimal parameterization of Km in this context is 5m, then points may deviate roughly 5m from the general neighborhood pattern before they are harshly penalized by the IoD. Points that have a neighbor-pair within 5m are thus considered roughly “ordered” by the IoD, while those with larger deviances are considered “disordered”. I clarified this in the text (3.2.1)

+ L284..285. Explain how the result obtained for a subset of the data (scale independence is assumed?) can be generalized to other cases (different scales).

This idea was poorly explained – the intent was to explain that characteristic scales in a dataset can be discerned through exploratory analysis of whole of the data or, if the scale is invariant throughout the data, through a part of it. The IoD is limited to quantifying order at one scale only; it cannot be used to quantify data that is ordered at multiple scales simultaneously or with a scale that changes greatly as a function of spatial location. Text has been added to section 3.2.1 to reflect this.

+ I did not understood Figure 7. Can you improve the explanation?

The explanation has been updated.

**Reviewer 3**

I liked reading this paper which offers a new index to quantify a particular concept of geometric disorder. I have several comments that try to make things more clear and highlight some aspects of the approach that are not explicitly developed.

The method is explained in Section 2. I had to read this section three times to get the idea of the new index. This section is poorly written and right now it brings lots of hidden or badly explained aspects of the method. Indeed, the paper novelty should be described here, and right now the reader gets into an overall confusion about the strategy followed.

Fair

Having said this, the papers comes often into mixing point patterns and continuous geostatistical patterns. Clearly, the presented method applies over points, but in some comments, and datasets it seems as if the points were sampled from a continuous field yielding a geostatistical pattern. This should be made clear.

The IoD is only applied to points in this paper, and the algorithm only works with datasets comprised of discrete point sets. I think R3 is referencing the fact that the synthetic data was derived essentially by distorting grid-like structures? We can emphasize that

In addition, there are a number of tunning parameters playing important roles in the building of the index. How the radii are selected to setup the neighbourhoods. Do they depend on the spatial structure of the point pattern? I believe they should.

I will add a section describing how to select the correct parameters. This is partially described in the results sections wherein it is proposed that an optimal *r* is the characteristic scale of the suspected pattern and *Km* is the expected intra-pattern noise. However, it is not explicitly stated that the algorithm’s ought to be tuned based in this information so we should do that

And talking about spatual structures, all I can see is different arrangements of points that are independent of each other, so the authors are working with inhomogeneous Poisson patterns. Is this right or am I missing something? because the method should be also tested against several structures and see how spatial interactions act on the behaviour of the index.

I am not exactly sure what is being suggested for us to do here. I definitely do not think that any of the data evaluated resembled a Poisson pattern, homogenous or otherwise, with the exception of the highly perturbed portions of the synthetic data but perhaps I am misunderstanding what a Poisson pattern is. But I’m not sure what is meant by testing the method against several structures – meaning structures beyond just Poisson patterns?

There are no connections between the new index and the concept of order/disorder given by complexity measures. There is an important line of research to which this paper should be linked. Complexity measures and Information theory seem to provide similar information in terms of order. Also some connection to fractality indexes should be considered. Stochastic geometry goes close to this aspect.

1. I am not sure what is meant by complexity measures or how it relates to the concept of geometric disorder – need to research
2. Dong (2000) uses lacunarity, a concept intricately related to fractality, as an order-sensing measure. This is discussed in the introduction – can be emphasized