Dear Editor, Professor Yuan,

Many thanks for your help for arranging the review process and facilitating the communications from the reviewers, we are grateful for your efforts.

In this revision, we went through the content and made some changes in the text to incorporate reviewer’s comments, in particular, we changed figure 4 (b), figure 5 and figure 6 with additional layers of centroids of workplace zones and airport fields in Great Britain to provide better geographic context of the derived boundaries. We also provided responses to address the reviewer’s comments with details enclosed below. Please take a look. Thanks again.

To all the reviewers,

We appreciate your help and we are grateful for your detailed feedback and efforts from both rounds to improve and better shape the manuscript. Please find our detailed responses to your specific comments blow.

Best Regards

Reviewers' Comments to Author:  
Reviewer: 1

Dear reviewer,

First of all, many thanks for your help and efforts for providing suggestions and feedback for both rounds of the review. Please see our responses below to your specific questions and comments, we hope it clarify the remaining concerns. Thanks again.

This is second round that I read this manuscript. The authors have almost extensively reworked their manuscript and have addressed reviewers’ comments.

It is interesting to see the innovative use of social media in this line of research. The authors carefully and methodologically prepared their social media. However, we still need to answer if the data collected is representative and reliable for the proposed research in absence of ground truth. The authors obviously were aware of this issue and give responses to the reviewers.

1. This study is the integration of previous work by Ratti et al. (2010) and Jurdas et al. (2015). The main different is that authors using new LBSM as a measure to analyze the pattern of human mobility. But what are major lessons learned from this work and the differs from previous works.

Dear Reviewer,

Thanks for the comment. Please let us clarify the differences between our paper and the mentioned two papers.

The related study Ratti et al. (2010) and Sobolevsky et al. (2013), among others showed that community detection in human interaction systems and mobility networks usually leads to connected spatially cohesive communities (even with no consideration of spatial configurations and constraints). This is mentioned in the manuscript that “A common outcome observed in the mentioned studies is that the strongly connected urban regions in the form of communities in the network space yield geographically cohesive areas, in spite of different community detection methods and various forms of social and physical human interactions were used.”

Few studies went further to explore the reasons that lead to such effects, but “a general consensus is that those geographically cohesive areas are instances of the effects on spatial proximity, where the interaction strength between two urban regions decreases as the geographical distance between them increases”. One of the major contribution in this paper is to explore the linkages between the spatial proximity effects and the characteristics of the underlying spatial interactions. To consider the geographical constraints in the interaction systems, in this study, we relied on investigating the physical movements of people (twitter users in this case) and built a mobility network to study the spatial interactions, which was achieved by looking for insights from the mobility patterns. During the process, we employed the methods developed in Jurdas et al. (2015) and we have applied to two scales (national level and city level) to make sure of the consistency.

In short, this paper differs from the mentioned two paper is not simply merging two ideas and replacing the dataset with social media data, but an exploration of the relations between the distance decay effects and spatial interactions, which serves the purpose of depicting urban boundaries from a mobility network of spatial interactions. By employing a gravity model, we can quantitatively reveal the spatial proximity in spatial interaction systems that interaction strength between two urban regions decreases as the geographical distance between them increases.

2. Why authors used Infomap algorithm to perform the community detection? What was the basis for selecting these algorithm? How about other algorithm, like Walktrap and Multilevel algorithms?

Dear Reviewer,

It is a great question that there are currently multiple forms of community detection methods. Because the network needs to be a direct weighted graph (we have illustrated in the supplement material), unfortunately, many of the existing methods do not work with directed graphs. In particular, we can direct it to an un-official web link for reference: <https://www.r-bloggers.com/summary-of-community-detection-algorithms-in-igraph-0-6/>

The two main popular methods found from the literature are modularity maximization based methods and Infomap, both of which we had compared and explained in the manuscript.

Specific comments

1. In section 4.1, “We then used these natural breaks within the mobility patterns to …”. For heavy-tailed distribution, head/tail breaks should be adopted for classification.

Jiang B. (2013), Head/tail breaks: A new classification scheme for data with a heavy-tailed distribution, The Professional Geographer, 65 (3), 482 – 494.

Dear reviewer,

Thanks for recommending this literature. Interestingly, we were aware of this line of work in terms of using ht- index as a classification scheme/principal when dealing with measurements with heavy-tailed distribution. However, there is a little bit confusion, in this case, in terms of the wording “natural breaks”, as it is often associated with the ht-index for producing hierarchy structures that reflect natural hierarchies (breaks) in many applications. We therefore changed the term to “distinct distance ranges” in the revision.

More importantly, in our case, the ht-index does not apply, since we are not visualizing the measurements (e.g., the displacements or radius of gyration). By the way, it could be well applied to visualize the movement flux illustrated in the supplement material, but it is out of the scope of this paper. Furthermore, as illustrated in the manuscript, three well fitted distributions were identified to identify the break, which is a statistical approach. For example, we have taken your advice to revisit the ht-index for the measurement of displacements (and radius of gyration). For displacements, if we use ht-index, the first mean is 5.89 km and second one is 50.32 km; for radius of gyration, the first mean is 32.92 km and second mean is 85.08 km, these values were not meaningful to separate different groups of users.

Reviewer: 2

Dear reviewer,

Many thanks for your help and efforts for providing suggestions and feedback for both rounds of the review. Please see our responses below to your concerns and suggestions. Thanks again.

The revision of this paper has improved and thanks for addressing most of my comments in the revision. My only remain concern is that findings of the paper are largely dependent on the data, and parameterization (e.g., selection of distance decay factor, fishnet cell size), and may not be generalizable to other regions.

Dear reviewer,

Thanks for the comments. This is very good insight that this case study was carried out in the regions of Great Britain with less certain datasets from social media data (in comparison with mobile phone datasets for human mobility research.). While we have discussed the advantages and disadvantages in both dataset, our major goal was to investigate the spatial proximity effects found in the physical spatial interaction systems. At the same time, because the Twitter data can provide relative large spatial coverage, we had relied on such dataset for the investigation.

In terms of parameter selection, we are expecting that the mobility patterns found in this paper would differ from the results in other regions of the world. However, the differences are expected to be the actual distance ranges identified in our case in comparison to the ones from Jurdas et al. (2015). In particular, because the availability of Twitter data, future studies can verify the variations. More importantly, we argue that this method of looking into detailed mobility pattern to explain the spatial proximity effects in spatial interaction systems can be applied and generalizable to other regions.

Since the human mobility is usually explained by local social-economic factors (e.g., working commuting; p. 13, line 34), it would be useful to provide additional maps or layers of business districts, and major landmarks (e.g., airport, green spaces) in Figures 4, 5,6 to help interpret the boundaries derived. It would also be useful for audiences that are not familiar with the geographic context in Great Britain to better understand the results.

Dear reviewer,

Many thanks for the suggestion, it makes sense to add additional layer of information to help readers to be better familiar with the geographic context in Great Britain.

For the revised figures, we had added the layer of airport fields and population-weighted-centroids of workplace zones as background information of the result layers. Note that, for figure 4, to avoid visual clutters, we only added airport fields in Figure 4 (b), while the mentioned two layers were added in Figure 5 when zoomed in more detailed regions.