Dear Editor, Professor Yuan,

Many thanks for facilitating the rapid review process and communications from the reviewers. We are very grateful for your efforts.

In this revision, we have addressed the comments by the reviewers. For example, we changed figure 4 (b), figure 5 and figure 6 by adding additional layers of centroids of workplace zones and airport fields in Great Britain to provide a better geographic context of the derived boundaries. More specific responses to the reviewers’ comments are as follows.

To all the reviewers,

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

Best Regards

Reviewers' Comments to Author:  
Reviewer: 1

Dear reviewer,

Many thanks again for your help and efforts for providing suggestions and feedback through both rounds of the review process. Please see our responses below to your specific questions and comments. We hope that this response can resolve the remaining concerns.

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.

The related studies by 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 without consideration of spatial configurations and constraints). This is mentioned in the manuscript that “A common finding from 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 spatial human interactions were used.”

Few studies went further to reveal 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 contributions of our 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, we investigated 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. To study the detailed mobility patterns, we employed the methods developed by Jurdas et al. (2015) and have applied to two scales (national and city) to assure the consistency.

In short, our work differs from the aforementioned two papers in that it is not simply merging two ideas and replacing the dataset with social media data, but a novel approach to characterizing 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.

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?

There are a number of community detection methods. While the network needs to be a direct weighted graph as we have illustrated in the supplement material, unfortunately, many of the existing methods do not apply to directed graphs. For example, this online reference: <https://www.r-bloggers.com/summary-of-community-detection-algorithms-in-igraph-0-6/> provides further details in this regard. The two main popular methods found from literature are modularity maximization based method 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.

Thanks for point out this work. Interestingly, we were aware of this line of work in terms of using ht- index as a classification scheme and principle when dealing with measurements with heavy-tailed distribution. However, this case might be confusing, in terms of the wording “natural breaks”, as it is often associated with the ht-index for producing hierarchical 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 the intent is not to visualize the measurements (e.g., the displacements or radius of gyration). Furthermore, as illustrated in the manuscript, three well-fitted distributions were considered to identify the break, which is a statistical approach. For example, we took 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 providing very helpful suggestions and feedback in both rounds of the review process. Please see our responses below to your concerns and suggestions.

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.

A primary goal of our research is to investigate the spatial proximity effects found in the physical spatial interaction systems. Because the Twitter data can provide relative large spatial coverage, we rely on such data for achieving the goal. We have discussed the advantages and disadvantages of using social media data in comparison with mobile phone data.

In terms of parameter selection, we would expect that the mobility patterns found in our paper would differ from 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, the parameters of distance decay factor and fishnet cell size were chosen based on the performing statistical analysis of the mobility patterns. For example, as illustrated in the London case, because there were no long distance ranges in the mobility pattern, we chose 1 km cell size based on the literature. Therefore, to apply our method in other regions, the exact values of parameter may vary from the ones in our study, we should perform statistical analysis to first identify the mobility patterns and choose corresponding parameters.

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.

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