Generating a Map of Well-being Regions Using Multiscale Moving Direction Entropy on Mobile Sensors

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Abstract

The well-being of individuals in a crowd is interpreted as a product of individuals crossing over from heterogeneous communities, via interactions with other crowds. Here, the index moving-direction entropy corresponding to the diversity of the moving directions of individuals is introduced to represent such an inter-community crossover and extended with multiscale scopes. Multiscale moving direction entropies, composed of various geographical mesh sizes to compute the index values, are used to capture the flow and interaction of information owing to human movements from/to various crowds. The generated map of high values of multiscale moving direction entropy was visualized, where the peaks coincided significantly with the preference of people to live in each region.

Introduction

The dimensions of social well-being have been discussed. Career, social, financial, physical, and community well-being, defined as the five factors of well-being (Rath 2010), are interrelated in that social relationships via interaction among communities create prosperity from physical and financial aspects and also affect individuals' health in both physical and mental aspects. Thus, in particular, we focus on social and community-based well-being. This focus is linked to the dynamics of crowds, considering the intra-crowd and inter-crowd contacts of individuals, which bring and create norms in society. Negative (Le Bon 2005, Postmes 1998) and positive (Manstead 1996, Reicher 2000) effects of crowds have been pointed out, of which a positive effect is the emergence of new norms from the communication of individuals from other crowds. The assumption here is that norms to be created in each crowd, via its interaction with other crowds or communities from which individuals may come, are the essence of all dimensions of well-being, where a crowd refers to a group meeting in a region with a specific location, whereas a community is a group of people sharing a common interest who may meet online. On this assumption, we focus on activities in which heterogeneous communities interact through inter-crowd contact.

To capture activities with inter-crowd contacts, we used human mobility data available from smartphones to compute the values of an index representing the diversity of directions in which individuals move in and across regions. As illustrated in Figure 1, the movements from/to regions of multiple scales are regarded as the physical dimensions of inter-crowd contacts. A heat map of regions on this index is the expected output, which implies the enhancement of inter-crowd activities.

Muti-scale Moving Direction Entropy

Moving direction entropy (MDE) was introduced as an index representing inter-community activities (Ohsawa 2023) computable from mobile data. Here, we introduce a multiscale MDE as an index to quantify the diversity of people moving in and across regions expected to urge inter-crowd contacts. The MDE in region r at time t is defined by Eqs.(1), where θ denotes the anticlockwise moving direction, discretized by segmenting 2π into 100 segments. $p_\theta(r, t)$ is the probability of an individual moving in the $[\theta, \theta+\pi/50]$ direction. The multiscale MDE was computed for small meshes, as shown in the central thick frame in Figure 1, as well as for large or larger meshes. $H_{\mathrm{MDE}}(r,t)$ was computed from the point data of human mobility collected using smartphone sensors provided by Agoop Inc..

$$H_{\mathrm{MDE}}(r,t) = -\sum_{i=1}^{100} p_{\theta=\frac{i\pi}{50}}(r,t)\, ln\, p_\theta(r,t) \qquad (1)$$

Results

Figure 2 shows the results for the area (E139.3-140.0, N35.5-35.85) in Tokyo. The peaks of the red heatmap were found to fit the blue dots showing the highly preferred residential regions, many of which were clustered in the most activated part of Tokyo. However, preferred stations, such as Hachioji and Kichijoji, which are not outstanding in the heatmap of high-MDE meshes for Δ= 100m as in (a), are highlighted substantially for Δ= 1km as in (b).

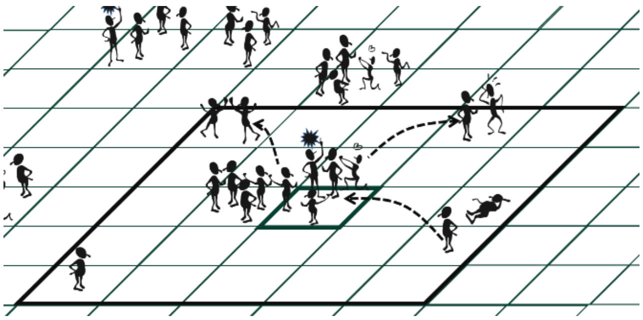

Figure 1. A hierarchical study approach to crowd dynamics. The multiscale index for a larger mesh shown by the larger thick frame and for the belonging small meshes are computed, and combined to study the macro-micro interaction.

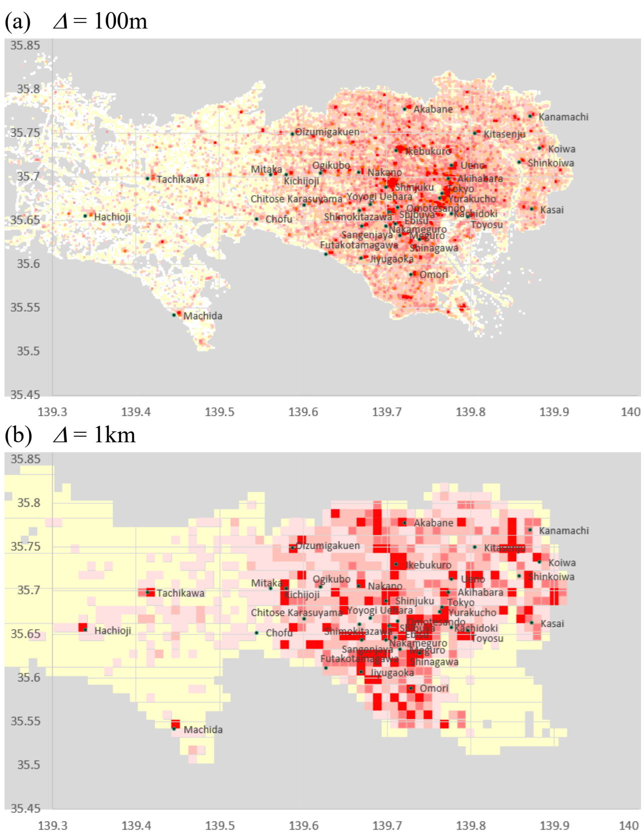

Figure 2: Red-color heatmap for the area showing the high-MDE regions, on which the black nodes show the 43 most highly preferred stations to live nearby: on three coupled datasets provided by Japanese estate companies (Haseko 2023, Suumo 2022, AT 2022).

Discussion and Conclusions

As in Fig 2, a larger Δ may generate a better map in the sense of completeness (recall of preferred residential regions). In contrast to Figure 2, we also found a result not included in the Results section: the recall of preferred residential regions was better for Δ =100m than for a larger Δ when we counted the meshes of the highest MDEs (not the peaks, i.e., local optimal, as in the heatmap in Figure 2). The reason for this inconsistency is in question, explanation expected by introducing the aspect of attention of habitats to peaks in their neighborhood. Considering the high recall result obtained by coupling the two figures in Figure 2, we can expect to generate a map of well-being crowds by a multiscale combination of high-MDE regions. Our future work will address the map generation of Nigiwai, defined as prosperous crowds but dealt with so far from physical aspects of distances between individuals (e.g. Abdelwahab 2021), extending by introducing dimensions of social prosperity to the well-being of crowds.

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