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Article

Statistical Law between Areas and Perimeters Created by a Moving Trajectory

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Abstract: Based on our interest in properties of human movement, we investigated Japanese GPS data, and arrived at the following three observations: 1) there is a strong correlation between the area of polygons created by human movement trajectories and their perimeters; 2) short-distance movement trajectories less than 5 km tend to enclose a large area like a circle; 3) long-distance movement trajectories over 5 km tend to be straight. We also clarified the following four observations on individual attributes and external factors related to long-distance movements: 1) women tend to travel more linearly than men; 2) linearity is stronger on weekends and national holidays in areas with a large theme park; 3) linearity is weaker on weekends and holidays in areas with many historical tourist attractions; 4) these variations are created by people visiting such areas. These properties should be incorporated when modeling the movement trajectories of humans.

Keywords: GPS data; human movement trajectories; individual attributes; external factors; linearity

1. Introduction

In recent years, the development of GPS and other location information systems has simplified and increased the accuracy of determining the position of various objects, including people and vehicles. The data obtained in this way are used to conduct new types of research in various fields, including traffic engineering, urban planning, disaster prevention, and behavioral pattern analysis. For example, a proposed method uses cell-phone location data to extract individual behavior patterns, which can then be exploited to identify movements within a city ([1–4]). The spatial distribution of base users is visualized by analyzing GPS data, and the characteristics of human flows and the location of bases are discussed ([5]). There is also research on the obstacles faced when people must flee to evacuation sites during natural disasters as well as efficient evacuation guidance using GPS-derived movement trajectory data ([6]). Furthermore, the actual damage and recovery process can be read from post-earthquake behavior patterns based on GPS information ([7,8]).

The analysis of human movement trajectories is fundamental to the study of human behavior, not only from a perspective directly related to these application fields. For example, animal migration tracks are critical from the perspective of environmental protection, even though their actual status is not fully understood; data collection using GPS and other methods is currently underway ([9]). In a recent study, around 100 domestic cats were tagged with GPS and analysis of their behavior patterns has begun ([10]). The complications required to attach GPS tags to animals is more cumbersome than one might imagine. Fortunately, sufficient data have already been gathered on humans who actively carry GPS tags as smartphones or cell phones. Both qualitatively and quantitatively using such data to investigate the characteristics of human behavior is fundamental for a deeper understanding of human beings.

Human movement distances are also known to follow a power distribution ([1]); various studies are based on this notion. For example, some studies describe the emergence of a power distribution as a superposition of such human modes of transportation as walking, running, and bicycling as well as other modes of transportation, including trains/subways, cars, cabs, and buses, all of which follow a log-normal distribution ([11]). Other studies link the power distribution of human movement

distances to the structure of social networks ([12]). The relationship between the area enclosed by a moving trajectory on a random walk and the distance traveled has also been studied using the concept of fractal dimension ([13–15]). In this paper, we show that various human behaviors can be analyzed from movement trajectories by investigating the well-known set of 2-dim area and 1-dim perimeter lengths without broaching such concepts.

From this viewpoint, we previously reported on the statistical properties observed in the correlation between the area and the perimeter of polygons drawn using confidential data on the daily movement trajectories of approximately 20,000 people passing through Urayasu City, Chiba Prefecture in August 2022 ([16]). We found that the movement trajectories of people traveling distances of 5 km or more are linear, and those traveling distances less than 5 km are enclosed in much more areas, varied such as circles and squares. This result suggests that long-distance travelers have a specific destination in mind to which they tend to move to and from in a straight line. Short-distance travelers have multiple destinations and tend to move in a trajectory that resembles a circle to minimize their travel distance.

In addition, we found that the linearity of long-distance travel was particularly strong in women under the age of 30, and that this tendency was particularly strong on weekends and national holidays. These results are thought to be influenced by the presence in Urayasu City of Tokyo Disneyland, Japan's largest theme park. In this paper, we analyze the movement trajectory data of Kyoto City, Japan's largest historical tourist city to confirm this assumption. We then confirm whether the same statistical properties are observed as in Urayasu City. We support this investigation by also analyzing the data on the movement of people in Kanazawa City, Ishikawa Prefecture, which is another historic tourist destination.

This paper is organized as follows. First, Section 2 describes the data used in this paper. Section 3 reviews the previous, relevant research. In Section 4, we examine whether the observation results (reviewed in Section 3) from Urayasu City in Chiba Prefecture can also be observed in the data from Shimogyo-ku in Kyoto City and Kanazawa City in Ishikawa Prefecture. In Section 5, we show that the observation result in the actual data described in this paper can be reproduced by a simple model simulation. Finally, Section 6 summarizes this paper and discusses future issues.

2. Data

Our analysis in this paper is based on the following three datasets purchased from Agoop Corp. One is the movement trajectory of people passing through Urayasu City, Chiba Prefecture in August 2022. Another is the movement trajectory of people passing through Shimogyo-ku, Kyoto in November 2021 and January 2022. One more is the movement trajectory of those passing through Ishikawa Prefecture in August 2023 and September 2023. Shimogyo-ku is in the heart of Kyoto City, including the busiest Kyoto's main train station. These movement trajectories consist of latitude and longitude data at one-minute intervals, with specifications that do not allow movements to be tracked across days. We analyzed approximately 20,000 trajectories per day, each of which consisted of five or more points and a distance less than 10 km between the start and end points.

For example, Figure 1 shows one person's movement trajectory through Urayasu City, Chiba Prefecture on August 27, 2022, where the start and end points are indicated by red and green markers (the latter is hidden behind the former). This is a typical example of what can be observed in a moving trajectory, where its area bounded is 28.2 km² and its perimeter is 200.4 km. Figure 2 shows another person's movement path through Urayasu City on August 22, 2022. This is another typical movement trajectory on a small scale, although it is overlooked when superimposed on Figure 1 due to the scale, which is an enclosed area of 0.033 km² whose outer perimeter is 0.70 km.

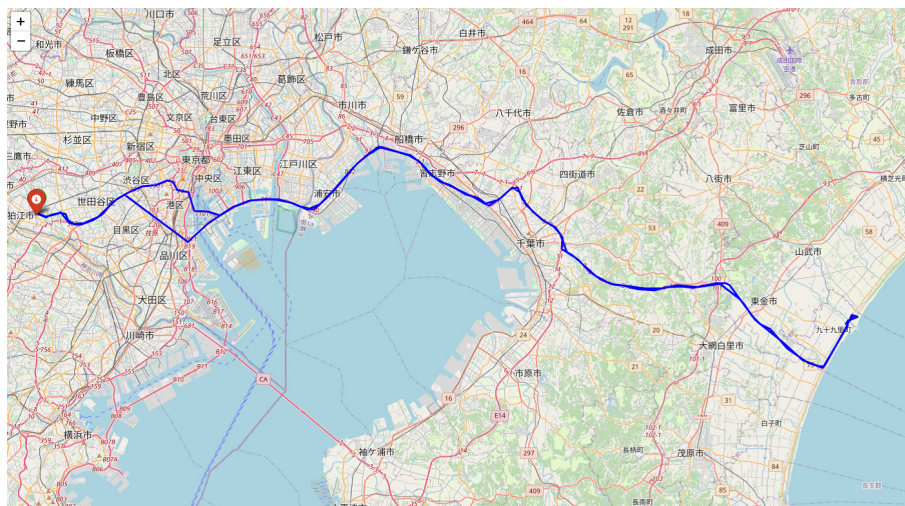


Figure 1. Person's movement trajectory through city of Urayasu City on August 27, 2022. Enclosed area is 28.2km^2 , and its perimeter is 200.4km .

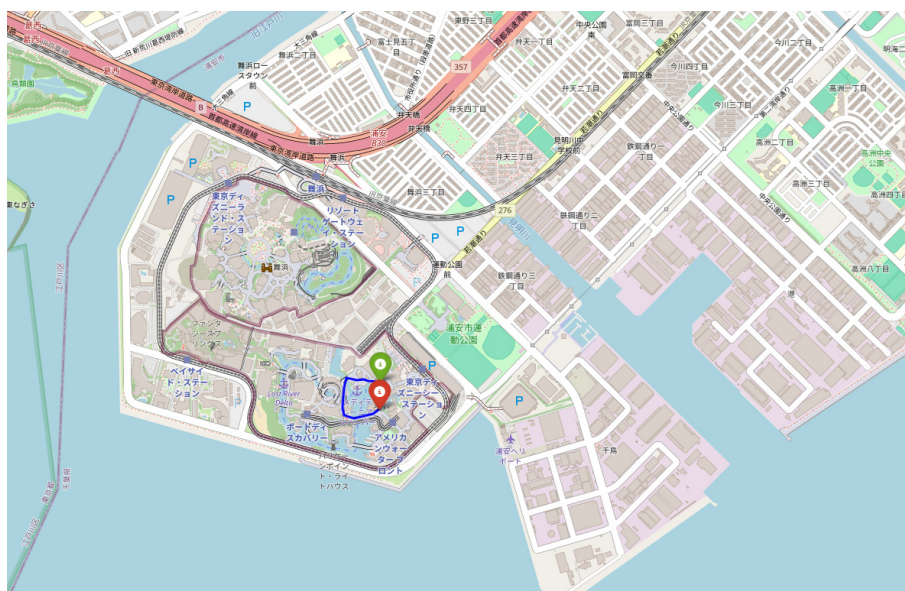


Figure 2. Person's movement trajectory through Urayasu City on August 22, 2022. Enclosed area is 0.033km^2 and its perimeter is 0.70km .

The database contains not only movement tracks but also such personal attributes as gender, age, and city code where a person is presumed to live. Residency estimates are made by data-providing vendors who can track movement across days. This paper focuses on whether the properties observed in Urayasu City can also be observed in data from Shimogyo-ku and Ishikawa Prefecture. In particular, we discuss what fuels the changing nature of long-distance travel on weekends and national holidays.

3. Analysis of Urayasu City

3.1. Analysis without Consideration of Personal Attributes

First, in this section, our analysis does not consider personal attributes. As in our previous study ([16]), we denote the area of the polygon enclosed by the human movement trajectory as $S\text{ km}^2$ and its perimeter as $L\text{ km}$. Figure 3 is a scatter plot of L and S of people passing through Urayasu City, Chiba Prefecture on August 7, 2022, where 14,492 data points are displayed. The parabolic boundary seen on the left edge of Figure 3 shows that S has an upper bound that depends approximately on L^2 .

This corresponds to the fact that the polygon that maximizes S when L is constant is a circle, and the relation is $S = L^2/4\pi$. This property is visualized as the outer circumference of a polygon drawn by a movement trajectory that comes close to a circle or a square (Figure 2).

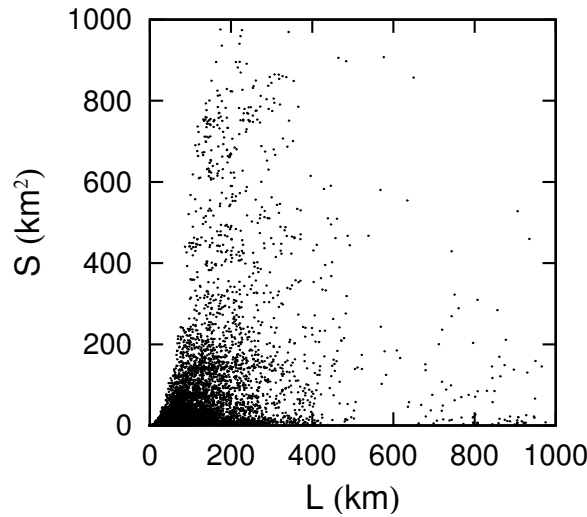


Figure 3. Scatter plot of perimeter L km and area S km² of polygon enclosed by movement trajectory of a person through Urayasu City on August 7, 2022.

Figure 3 also shows that the data are widely distributed, although many are gathered in $L < 200$ km and $S < 200$ km². To see the structure in more detail, we plot Figure 3 on both the logarithmic axes and denote it as Figure 4. It shows a strong correlation between $\log_{10} L$ and $\log_{10} S$, which can be expressed using parameter α :

$$\log_{10} S = \alpha \log_{10} L + \text{Const} . \quad (1)$$

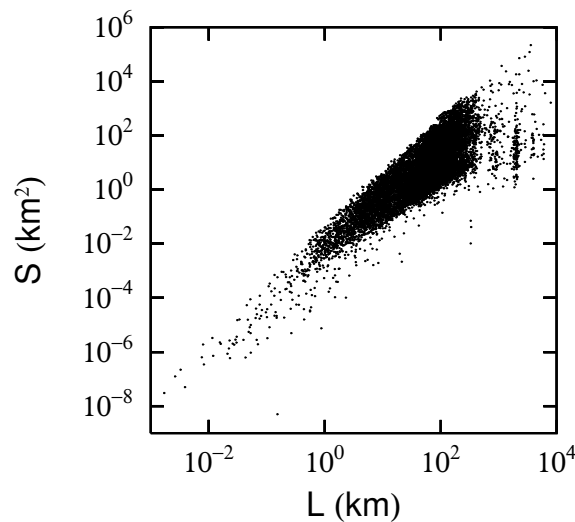


Figure 4. Figure 3 on both logarithmic axes

Furthermore, Figure 4 shows that parameter α in Eq. (1) is different for large (long distance) and small (short distance) scales of L . In this paper, we denote $L < 5$ km as a short distance and its parameter as α_{Short} and $5 \text{ km} \leq L$ as a long distance and its parameter as α_{Long} . The boundary between short and long distances, 5 km, was set as the distance an average adult might walk in approximately one hour.

Measuring those parameters by the least squares method for the data in Figure 4 yields $\alpha_{\text{Short}} = 2.05 \pm 0.03$ and $\alpha_{\text{Long}} = 1.40 \pm 0.01$. The fact that α_{Short} is close to 2 indicates that when the distance of the outer perimeter is less than 5 km, many movement trajectories will be polygons with a large enclosed area (Figure 2). On the other hand, α_{Long} falls between 1 and 2, indicating that many movement trajectories are straight and partially polygonal when the outer perimeter's distance exceeds 5 km (Figure 1). We use the fact that when the movement trajectories are all straight lines, area S of a rectangle with L , which is sufficiently large compared to 1, can be approximated as $1 \times (L - 1) \sim L$.

Next we measure parameters α_{Short} and α_{Long} for every person who passed through Urayasu City during the 31 days of August and represent these changes in Figure 5. We removed the errors (to two decimal places) for clarity. There are four minima in $\alpha_{\text{Long}}(\triangle)$ shown in Figure 5: August 7, 12, 21, and 30. August 7 and 21 are Sundays, the 12th is the second day of a period of summer holidays in Japan, and the 30th is just before the end of the children's summer vacation. The above observation indicates that people's long-distance movement trajectories are more linear on weekends and holidays.

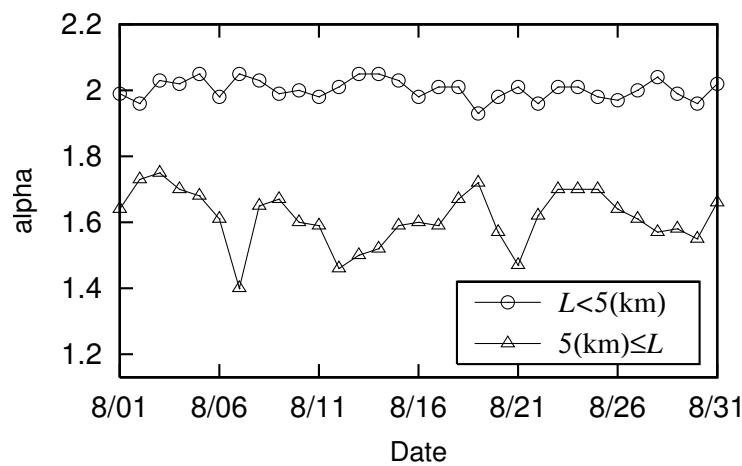


Figure 5. Changes in α_{Short} and α_{Long} of those passing through Urayasu City in August 2022: August 7, 14, 21, and 28 are Sundays; August 11 is a national holiday.

3.2. Analysis Classified by Personal Attributes

We next observed the movement trajectories classified by personal attributes. First, we note whether any differences surface by gender in long-distance movement trajectory parameter α_{Long} . Figure 6 shows the α_{Long} transition for women ($\triangle$) and men ($\circ$). At the same time, the transition for the case without a gender distinction is also denoted by a solid line ($-$), which is identical to the $\alpha_{\text{Long}}(\triangle)$ transition in Figure 5. Figure 6 shows that the α_{Long} of women is always smaller than that of men, an observation that implies that long-distance movement trajectories are more linear for women than men.

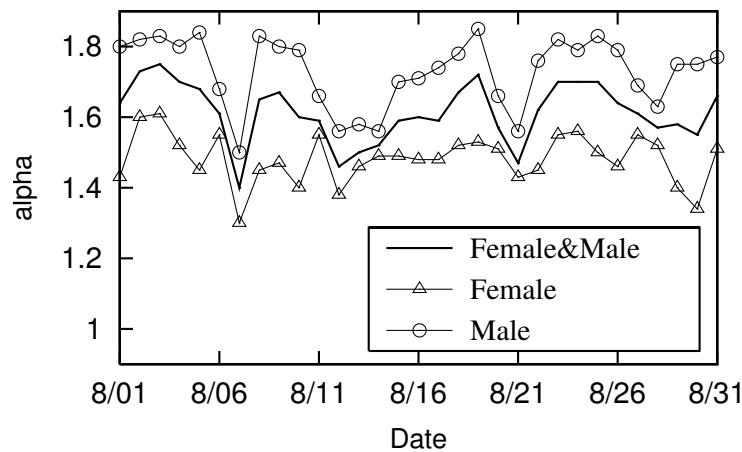


Figure 6. Women, men, and both genders together α_{Long} passing through Urayasu City in August 2022: August 7, 14, 21, and 28 are Sundays; August 11 is a national holiday.

We next categorized the ages into three groups: under 30, between 30 and 60, and over 60 (G1, G2, and G3). We examined whether long-distance migration parameter α_{Long} differed across these three groups. Figure 7 shows the α_{Long} trends for each group. The transition without age distinction is also marked with a solid line (—), identical to the α_{Long} (Δ) in Figure 5 and the α_{Long} transition (—) in Figure 6. Figure 7 shows that the long-distance movement trajectories for ages less than 30 (G1, Δ) are the most linear. It also shows no significant difference in the shape of long-distance movement trajectories for ages between 30 and 60 (G2, $\circ$) and 60 and older (G3, $\square$).

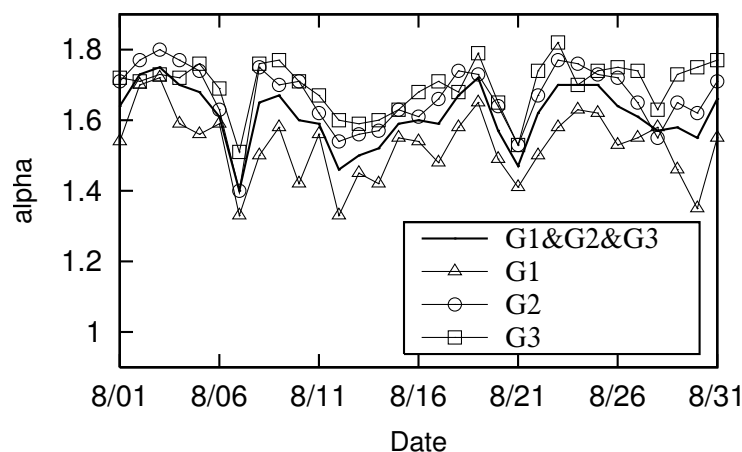


Figure 7. Changes in α_{Long} through Urayasu City in August 2022 for persons under 30 (G1), between 30 and 60 (G2), and over 60 (G3), and α_{Long} for them together: August 7, 14, 21, and 28 are Sundays; August 11 is a national holiday.

4. Analysis of Kyoto City

4.1. Analysis without Consideration of Personal Attributes

In the previous section, we observed how the statistical relationship between the area and perimeter of polygons enclosed by human movement trajectories depends on the environment (weekdays or holidays) and such individual attributes as gender and age. In this section, we confirm whether the

observation results from Urayasu City are similarly observed in other areas in Japan. This observation allows us to determine whether the observations in the previous section are altered by such external factors as region. Our analysis focuses on the movement trajectory of people through Shimogyo-ku, which is in the central area of Kyoto City where thousands of tourists visit many historical tourist attractions.

Figure 8 shows the $\alpha_{\text{Short}}(\bigcirc)$ and $\alpha_{\text{Long}}(\triangle)$ of people passing through Shimogyo-ku, Kyoto during the 30 days of November 2021. In Figure 8, as in Figure 5, the second decimal place errors were omitted for clarity. In Figure 8, $\alpha_{\text{Short}}(\bigcirc)$ remains close to 2, as in Figure 5, which shows the movement trajectory of Urayasu City. At the same time, $\alpha_{\text{Long}}(\triangle)$ falls between 1 and 2. However, the difference is that α_{Long} fluctuated around 1.6 in the case of Urayasu City, whereas it fluctuated around 1.4 for Shimogyo-ku. The major difference is that the linearity of the long-distance movement trajectory in Urayasu City is strengthened on weekends and national holidays (α_{Long} becomes smaller), and it weakens in Shimogyo-ku (α_{Long} becomes larger). Specifically, α_{Long} in Figure 8 has six maxima: November 3, 7, 13, 21, 23, and 28. These are all weekends or holidays (November 7, 14, 21, and 28 are Sundays; November 3 and 23 are national holidays). Similar results to the above can be found in the movement trajectory of those passing through Shimogyo-ku in January 2022.

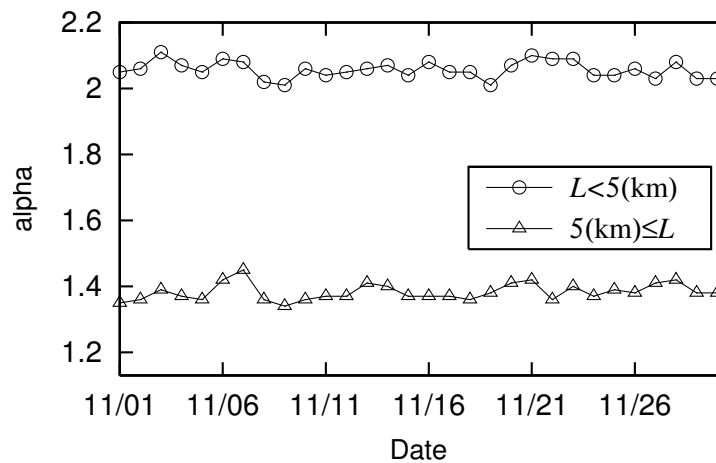


Figure 8. Changes in α_{Short} and α_{Long} of those passing through Shimogyo-ku, Kyoto in November 2021: November 7, 14, 21, and 28 are Sundays; November 3 and 23 are national holidays.

4.2. Analysis Classified by Personal Attributes

Figure 9 shows the α_{Long} transition for each woman ($\triangle$) and man ($\bigcirc$) who passed through Shimogyo-ku, Kyoto in November 2021. Transitions when gender is not distinguished are also marked with a solid line ($-$), identical to the $\alpha_{\text{Long}}(\triangle)$ transition in Figure 8. Figure 9 shows that the long-distance movement trajectory is more linear for women ($\triangle$) than for men ($\bigcirc$), as in Urayasu City.

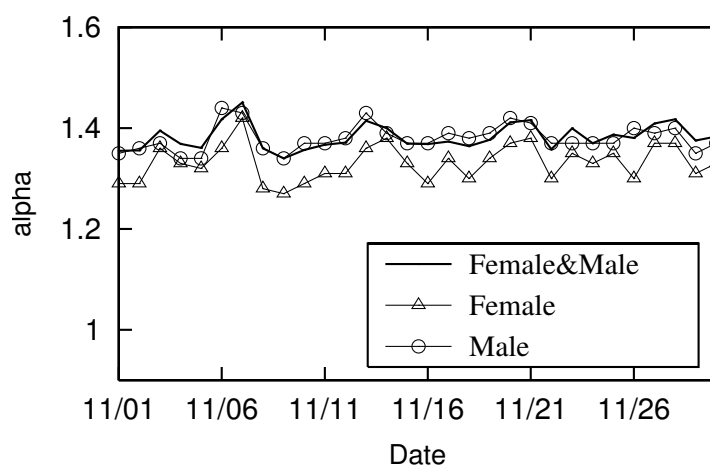


Figure 9. Changes in α_{Long} for women, men, and both genders combined through Shimogyo-ku, Kyoto in November 2021: November 7, 14, 21, and 28 are Sundays; November 3 and 23 are national holidays.

Next we examined whether long-distance movement parameter α_{Long} differed by age group (as in Urayasu City) by again classifying the people into the same three age groups: under 30, between 30 and 60, and over 60 (denoted as G1, G2, and G3, respectively). Figure 10 shows the α_{Long} trends by the three age groups. The transition when age is not distinguished is also marked with a solid line (–), identical to the $\alpha_{Long}(\triangle)$ in Figure 8 and the $\alpha_{Long}(-)$ transition in Figure 9. Figure 10 shows that in the case of Kyoto City, unlike Urayasu City, no significant differences are found in the shape of the long-distance movement trajectories by age group. Similar results to the above are observed in the movement trajectory of those who passed through Shimogyo-ku, Kyoto in January 2022.

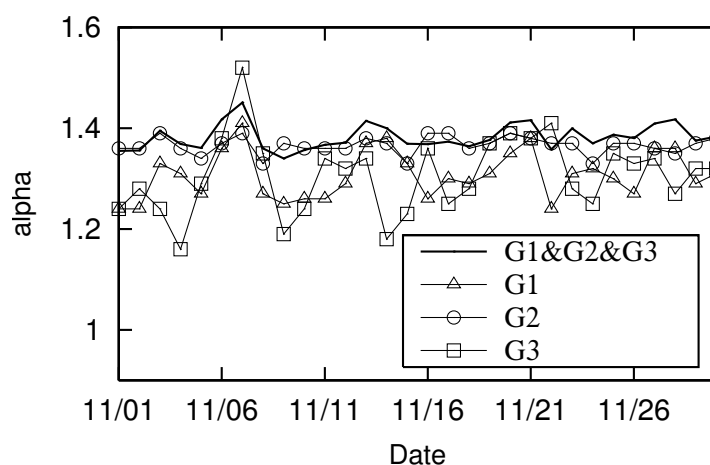


Figure 10. α_{Long} of people under 30 (G1), between 30 and 60 (G2), and over 60 (G3), and α_{Long} of them together through Shimogyo-ku, Kyoto in November 2021: November 7, 14, 21, and 28 are Sundays; November 3 and 23 are national holidays.

5. Factors Contributing to Long-Distance Variations

In the previous section, we compared the movement trajectory parameters (α_{Short} and α_{Long}) for two areas: Urayasu City, Chiba Prefecture and Shimogyo-ku, Kyoto City. The common property shared by both is that parameter α_{Short} of the short movement trajectory is around 2 in both cases, while long-distance movement trajectory parameter α_{Long} is between 1 and 2. In other words, short-distance

movement trajectories tend to enclose a larger area, and long-distance movement trajectories tend to be more linear, as observed in the two regions. However, α_{Long} was around 1.6 in Urayasu City and around 1.4 in Kyoto City. This means that the movement trajectory of a person passing through Shimogyo-ku, Kyoto is more linear with respect to the movement trajectory of a person passing through Urayasu City. The property, which differed significantly between the two, was that α_{Long} became smaller on weekends and holidays in Urayasu City, and it increased in Kyoto City. In other words, on weekends and holidays, long-distance movement trajectories are more linear in Urayasu City and less linear in Kyoto City.

In this section, we discuss what personal attributes create this variation in long-distance movement trajectories on weekends and holidays. We focus on places of residence and denote these data as a personal attribute, just like for the gender and age groups.

Figure 11 shows three transitions: 1) α_{Short} and α_{Long} for those who passed through Shimogyo-ku, Kyoto in November 2021 (Figure 8, solid lines around 2 and 1.4); 2) α_{Short} and α_{Long} for those whose homes (residences) are estimated to be in Shimogyo-ku, Kyoto ($\triangle$); 3) α_{Short} and α_{Long} for those whose homes are estimated to be outside of Shimogyo-ku, Kyoto ($\circ$). Figure 11 shows that the variation in long-distance movement trajectories ($-$) is made by those whose homes are estimated to be located outside of Shimogyo-ku, Kyoto ($\circ$). This strong correlation has a correlation coefficient of 0.99. Conversely, the correlations with the movement trajectories ($\triangle$) of those whose homes are estimated to be in Shimogyo-ku, Kyoto is very weak: a correlation coefficient of 0.18. The long-distance movement trajectories in Shimogyo-ku are comprised of an average of 18,888 persons per day. Among them, those whose homes are estimated to be in Shimogyo-ku ($\triangle$) average 1,284 per day. On the other hand, those whose homes are estimated to be outside of Shimogyo-ku ($\circ$) are 17,602 on average per day. Therefore, it is reasonable to assume from these numbers that the overall long-distance movement parameter α_{Long} is heavily influenced by those whose homes are estimated to be outside of Shimogyo-ku ($\circ$).

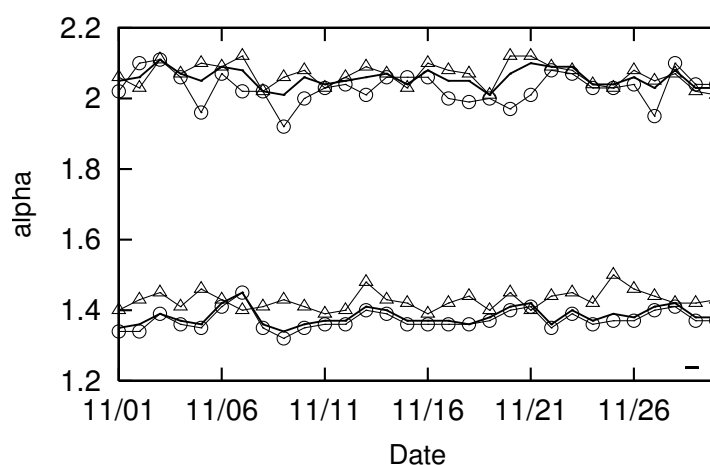


Figure 11. Changes in α_{Short} and α_{Long} for those who passed through Shimogyo-ku, Kyoto in November 2021 (solid lines around 2 and 1.4): The α_{Short} and α_{Long} trends are for those whose homes are estimated to be in Shimogyo-ku, Kyoto ($\triangle$), and the α_{Short} and α_{Long} are for those whose homes are estimated to be outside of it ($\circ$). November 7, 14, 21, and 28 are Sundays; November 3 and 23 are national holidays.

Next, we consider the same aspect for Urayasu City, as discussed in Section 3. Figure 12 shows the following three changes: 1) α_{Short} and α_{Long} of people who passed through Urayasu City in August 2022 (shown in Figure 5, solid lines around 2 and 1.6); 2) α_{Short} and α_{Long} of people whose homes are estimated to be in Urayasu City ($\triangle$); 3) α_{Short} and α_{Long} for those whose homes are estimated to be outside of Urayasu City ($\circ$). Figure 12 shows that, as in the case of Kyoto, those whose homes are

estimated to be located outside of Urayasu City ($\bigcirc$) are making the variation in the long-distance movement trajectories of those who went through Urayasu City. As in the case of Kyoto, the correlation is very strong: 0.99. Conversely, the correlation with the movement trajectory ($\triangle$) of those whose homes are estimated to be in Urayasu City is weak: 0.39. The long-distance movement trajectory in Urayasu City is comprised of an average of 14,257 persons per day. Among them, those whose homes are estimated to be in Urayasu City ($\triangle$) averages 2,733 per day. On the other hand, those whose homes are estimated to be outside of Urayasu City ($\bigcirc$) average 11,523 per day. Therefore, it remains reasonable to assume from the numbers that overall, long-distance movement parameter α_{Long} is greatly affected by those whose homes are estimated to be outside of Urayasu City ($\bigcirc$).

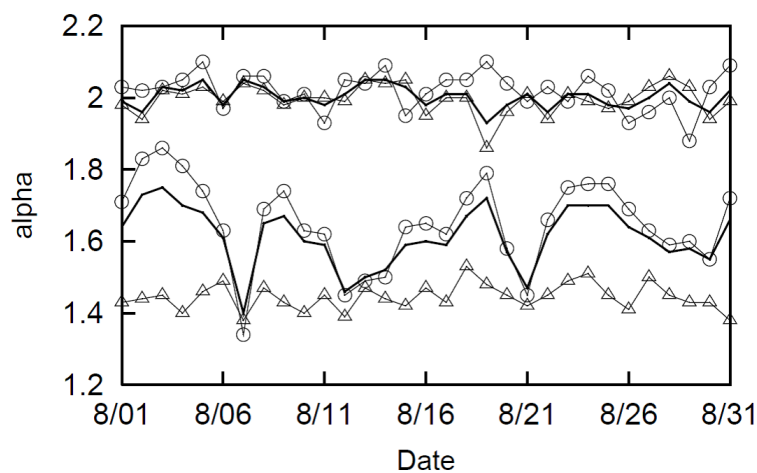


Figure 12. Changes in α_{Short} and α_{Long} for those who passed through Urayasu City in August 2022 (solid lines around 2 and 1.6): Among them, α_{Short} and α_{Long} trends are for those whose homes are estimated to be in Urayasu City ($\triangle$), and α_{Short} and α_{Long} are for those whose homes are estimated to be outside Urayasu City ($\bigcirc$). August 7, 14, 21, and 28 are Sundays; August 11 is a national holiday.

Furthermore, consider the same aspect about Kanazawa City, Ishikawa Prefecture. Figure 13 shows the following three changes: 1) α_{Short} and α_{Long} of people who passed through Ishikawa Prefecture in September 2023 (solid lines around 2 and 1.5); 2) α_{Short} and α_{Long} of people whose homes are estimated to be in Kanazawa City, Ishikawa Prefecture ($\triangle$); 3) α_{Short} and α_{Long} for those whose homes are estimated to be outside of it ($\bigcirc$). When movement trajectories are divided between those whose homes are presumed to be in Ishikawa Prefecture and those whose homes are not, most people are included in the former group. This differs from Shimogyo-ku, Kyoto, and Urayasu City, where many are from outside these areas. Therefore, unlike Urayasu City or Shimogyo-ku, people's residences are limited to Kanazawa City, where tourist attractions in Ishikawa Prefecture are concentrated. Figure 13 shows that those whose homes are estimated to be outside of Kanazawa City ($\bigcirc$) are creating the variations in the long-distance movement trajectories of those who passed through Ishikawa Prefecture. The correlation is strong: 0.86. Conversely, the correlation with the movement trajectory ($\triangle$) of those whose homes are estimated to be in Kanazawa City, Ishikawa Prefecture is weak: 0.19.

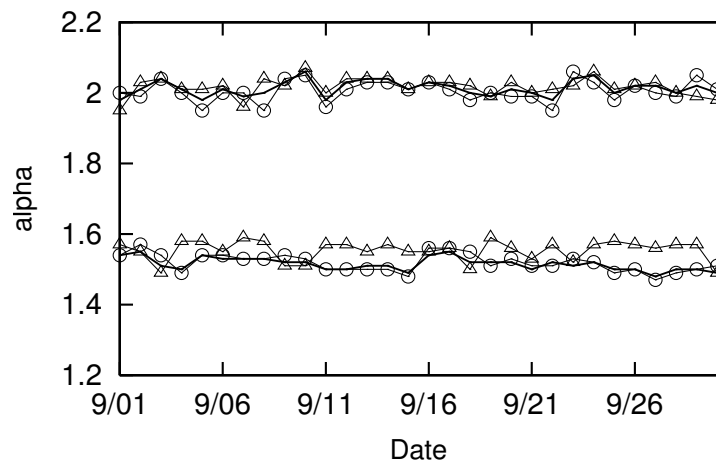


Figure 13. Changes in α_{Short} and α_{Long} for those who passed through Ishikawa Prefecture in August 2022 (solid lines around 2 and 1.5): Among them, the α_{Short} and α_{Long} trends are for those whose homes are estimated to be in Kanazawa City, Ishikawa Prefecture (Δ), and the α_{Short} and α_{Long} are for those whose homes are estimated to be outside Kanazawa City, Ishikawa Prefecture ($\circ$). September 3, 10, 17, and 24 are Sundays; September 8 is a national holiday.

The long-distance movement trajectory in Ishikawa Prefecture is comprised of an average of 16,382 people per day. Among them, those whose homes are estimated to be in Kanazawa City Prefecture (Δ) average 6,816 per day. On the other hand, those whose homes are estimated to be outside of Kanazawa City ($\circ$) are 9,563 on average per day. The number of people whose homes are estimated to be outside of Kanazawa City ($\circ$) is around 1.4 times the number of people whose homes are estimated to be in it (Δ); the correlation coefficient is around 4.5 times. In other words, it is not simply the number of people coming from outside the region that affects the overall long-distance movement parameter α_{Long} . It is also important that they are coming from outside the region.

At the end of this section, we also discuss the variation of short movement trajectories. Figures 11 and 12 show that those whose homes are estimated to be in the region (Δ) are creating the variation in short-distance movement trajectories. Their correlations are also strong: 0.79 or 0.88, respectively. The correlations with the movement trajectory ($\circ$) of those whose homes are presumed to be outside the region are weaker: 0.55 or 0.24, respectively. The number of people estimated to have homes in Shimogyo-ku, Kyoto is around 1.2 times that of those who do not, and the number of people estimated to have homes outside of Urayasu City, Chiba is around 5.2 times that of those who do not. In other words, it is reasonable to assume that the variation in these short-distance movement trajectories is created by people living in the region, given their numbers. Figure 13 also shows the difficulty of determining whether those whose homes are presumed to be in Kanazawa City, Ishikawa Prefecture (Δ) ($\circ$) are making short movement trajectories through it. The correlation coefficient between the former (Δ) and the total is 0.75, and the correlation between the latter ($\circ$) and the total is 0.82. Since the number of people whose homes are estimated to be in Kanazawa, Ishikawa is around 1.1 times the number of those whose homes are not, this result is also reasonable, given the numbers. The above conclusion indicates that short movement trajectories are made by local residents.

6. Simulation

In the previous sections, we identified statistical properties that can be found in the movement trajectory data of Urayasu City, Chiba Prefecture, Shimogyo-ku, Kyoto City, and Ishikawa Prefecture. The main feature is that area S of the polygon surrounded by the movement trajectories seems correlated to the power of its perimeter L ($S \propto L^\alpha$, Eq. (1)). This correlation is separated into short

and long distances. The power exponent (α_{Short}) at short distances with $L < 5(\text{km})$ is greater than the value (α_{Long}) at long distances with $L \geq 5(\text{km})$:

$$\alpha_{\text{Short}} > \alpha_{\text{Long}}. \quad (2)$$

In this section, we show that a model in which such a phenomenon occurs can be made with minimum tooling requirements.

First consider a circle whose radius r_{max} is centered at point B at distance R from point A (Figure 14). Take n points on its circumference. Denote by θ_i ($i = 1, 2, \dots, n$) angle AB , which makes a line connecting them and the circle's center B , where $0 < \theta_1 < \theta_2 < \dots < \theta_n < 2\pi$. Consider point C_i on each line whose distance from point B is r_i ($0 < r_i \leq r_{\text{max}}$). Figure 14 is an example for $n = 5$. Next, R is generated 20,000 times with a power distribution of exponent 1 and θ_i and r_i are uniformly distributed. Then, deeming point A as home and point C_i as a destination, we investigate the movement trajectory that connects $A \rightarrow C_1 \rightarrow C_2 \rightarrow \dots \rightarrow C_n \rightarrow A$ and measure area S that encloses it and its perimeter L . Figure 15 is a scatter plot of L and S with $r_{\text{max}} = 10$.

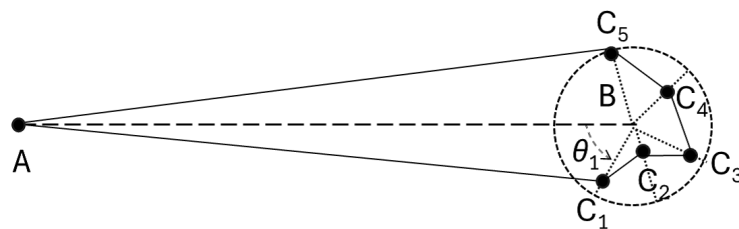


Figure 14. Consider a circle with radius r_{max} centered at point B at distance R from home A . Take n points on the circumference, and let AB be angle θ_i ($i = 1, 2, \dots, n$) between the line connecting them and center B of the circle. Furthermore, consider point C_i on the line whose distance from point B is r_i , where $0 < r_i \leq r_{\text{max}}$. The figure shows an example for $n = 5$.

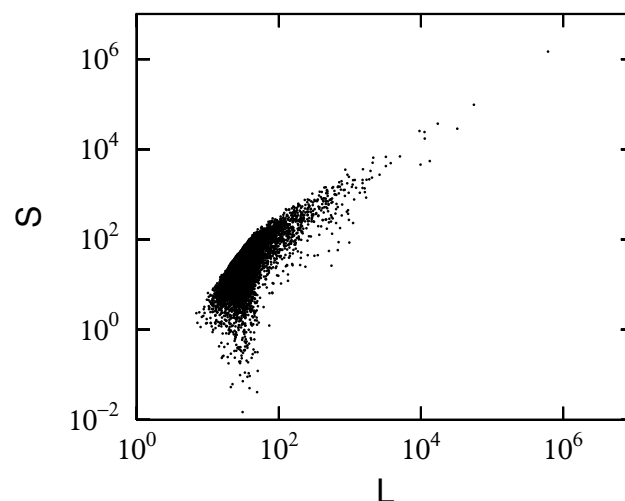


Figure 15. In setting of Figure 14, R was generated 20,000 times with a power distribution with exponent 1, θ ($0 < \theta < 2\pi$) and r ($0 < r \leq r_{\text{max}}$) with a uniform distribution. Consider the movement trajectory connecting $A \rightarrow C_1 \rightarrow C_2 \rightarrow \dots \rightarrow C_n \rightarrow A$. Scatter plot of polygon's area S and its perimeter L . Here, $r_{\text{max}} = 10$.

As seen from Figure 15, there is a two-fold linear correlation between $\log_{10} L$ and $\log_{10} S$, as in the actual data; its slope α is larger in the small range than in the large range of L . For example, if the boundary between long and short distances is $L = 20\pi$, then $\alpha_{\text{Short}} = 2.02 \pm 0.04$ and $\alpha_{\text{Long}} =$

1.13 ± 0.01 from the least squares method. If the boundary is $L = 10\pi$, then $\alpha_{\text{Short}} = 1.90 \pm 0.02$, $\alpha_{\text{Long}} = 0.98 \pm 0.02$. In both cases, the values of α_{Short} are around 2 and those of α_{Long} are between 2 and 1. Note that if $r_{\text{max}} \ll 1$ (e.g., $r_{\text{max}} = 0.01$), then α_{Short} is not observed. That is, r_{max} is creating the fold in the linear correlation, and its scale is approximately given by $L \sim 2\pi r_{\text{max}}$. In this simulation, R was generated with a power distribution, but the same phenomenon can be observed when generated with a uniform distribution. To simplify distinguishing here between long- and short-range boundaries, we use a power distribution. The above simple model allows the separation of correlations between $\log_{10} S$ and $\log_{10} L$ to be generated by the size of L .

The major difference between the scatter plot in Figure 3 in the actual data and Figure 15 in the simulation is that in the former data, the long-distance data are larger than the short-distance data; the opposite is true in the simulation. As noted in our Introduction, human movement distances are generally power-distributed. The data used in our analysis, however, were collected using the GPS function of smart phones possessed by those passing through regions containing tourist attractions. Because of this restriction, the movement trajectories of those who made long-distance movements are preferentially collected, and perhaps the amount of data due to the size of L is inverted between Figs. 3 and 15.

7. Results and Conclusions

This paper uses movement trajectory data for one month in Urayasu City, Chiba Prefecture, two months in Shimogyo-ku, Kyoto City, and two months in Ishikawa Prefecture to reveal the following observations. When a human's movement trajectory creates a polygon, statistical properties exist for its area and perimeter. When the distance is less than 5 km, which is the distance a typical healthy adult walks in approximately one hour, it is considered a short distance, and a distance exceeding 5 km is considered a long distance. The movement trajectories for short distances tend to resemble a large enclosed area like a circle, and the movement trajectories for long distances tend to be linear. These results can be understood from the slope of an optimal straight line drawn on a log-log scatter plot, which charts the area of a polygon drawn by a movement trajectory and its perimeter. For short distances, the exponent is around 2 and between 1 and 2 for long ones. These observations are common to the above three types of movement trajectory data.

We also identified the following facts by classifying these observations by individual attributes. Women tend to move more linearly than men. For Urayasu City, Chiba Prefecture, those under 30 tend to move more linearly than other age groups. For Shimogyo-ku, Kyoto, and Ishikawa, we found no significant difference in trends by age groups.

By comparing observations from three different regions in Japan, Urayasu City, Chiba Prefecture, Shimogyo-ku, Kyoto City, and Ishikawa Prefecture, we observed the impact of such external factors as region on statistical properties. First, the short-distance movement trajectory index was 2.00 ± 0.03 in Urayasu City, 2.06 ± 0.03 in Shimogyo-ku, and 2.01 ± 0.02 in Ishikawa Prefecture. All of these values are in the 2 range, and we observed no significant differences. However, the long-distance movement trajectory indexes varied by region, ranging from 1.61 ± 0.08 in Urayasu City to 1.38 ± 0.03 in Shimogyo-ku and to 1.52 ± 0.02 in Ishikawa Prefecture. The long-distance movement index showed a characteristic pattern of fluctuation: on weekends and national holidays, the index was smaller in Urayasu City and larger in Shimogyo-ku.

We interpret the above observations as follows. The difference in long-distance movement trajectory parameter α_{Long} for those passing through Urayasu City and Shimogyo-ku is due to the difference in the linearity of the movement trajectories of visitors from outside their respective regions. Disneyland, Japan's largest theme park, is in Urayasu City and attracts young women, especially on weekends and holidays. This situation strengthens the linearity of weekends and holidays.

On the other hand, the numerous historical tourist attractions in Shimogyo-ku attract people of all ages with an even stronger force. The linearity is moderated by the trajectory of people who want to efficiently visit many tourist destinations on weekends and holidays. The long-distance movement

trajectories of those passing through Ishikawa Prefecture are made by people who most likely live outside of Kanazawa City. Since tourist destinations in Kanazawa City are clustered in a smaller region than those in Kyoto City, it is difficult to observe a trend of moderate linearity on weekends and holidays. But compared to Urayasu City, the trend resembles that of Shimogyo-ku. We also found that the variation in the short-distance movement trajectory parameters is created by those living in the area.

Finally, the correlation parameter between the area and the perimeter of the polygon enclosed by movement trajectories differs between long- and short-distance movements. We can reproduce this property by a simple model simulation. This paper shows that discussions of movement trajectories, which have traditionally been described using such concepts as fractal dimension, can be analyzed by merely correlating two familiar variables: an area and its perimeter. The findings obtained by this paper include important properties that should be addressed when creating movement trajectory models.

Future work will spatially and temporally expand our analysis for the three regions in this study. However, obtaining commercially available human flow data faces financial constraints. It would be interesting to shift the perspective a bit from human flow data and use car navigation data to determine whether similar statistical regularities exist in the movement trajectory of cars. Furthermore, if we analyze the movement trajectories of non-human animals, we might identify differences between them and humans and increase our comprehension of human behavior compared with non-human animals. We are currently preparing to embark on a study in this direction and will report in the near future.

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