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# Evaluating the Brownian Bridge Movement Model to Determine Regularities of People's Movements

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**Abstract**

The movements of animals or humans are characterized by starting points, transitions and end points, where starting and end points typically represent distinct locations. Knowledge of such locations and movement patterns is relevant to predict future movements or to detect regularities in movement behaviour. We present a Brownian bridge-based approach applied to human movement data to extract regularities of people staying in distinct locations. Such information is, for example, of interest in zoology (e.g. animal home range estimation) or health (e.g. detection of deviations from regular behaviour of people with cognitive impairments). To obtain information about where a person stayed, we derived the areas of their whereabouts from GPS trajectories by using a Brownian bridge movement model (BBMM). The resulting whereabouts areas were intersected with these GPS trajectories to create so-called whereabouts tables, which describe time of day, duration and place of a person's stay. The probability of finding a person in a particular area within a particular time window was determined. The whereabouts areas of two people were investigated and assessed by using two tailored quality measures: spatial accuracy and spatial uniqueness. In order to reduce the computational costs of BBMM, down-sampling was investigated. With respect to spatial accuracy, results improved by down-sampling.

**Keywords:**

brownian bridge movement model, whereabouts area, whereabouts range, time cycle

## 1 Indroduction

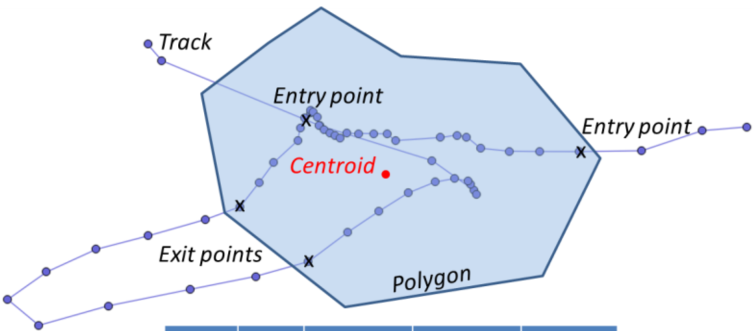
Predictive models for the movement of animals date back to the 1970s (e.g. Van Winkle, 1975). In those days, movement records were based on on-site observations and were recorded manually. With the advent of GPS technology, the recording of movements became a topic of interest also in research dealing with human behaviour (Preisler et al., 2004; Shih et al., 2015; Turchin, 1998). As technology improved over the years, data collection and the reconstruction of trajectories became more and more advanced, and there was a surge in interest among researchers wanting to model movement behaviour. One way to understand movement behaviour is to describe it as a set of stays in some small whereabouts ranges and movement between these whereabouts ranges. The whereabouts ranges represent starting and endpoints of movement, and this is where essential behavioural information can be gathered. In animal ecology, the application of such movement models is a very lively research area. For instance, there are many approaches to estimate animals' so-called home ranges in order to determine the locations in which the animals are likely to be found (Powell & Mitchell, 2012; Van Winkle, 1975; Walter et al., 2011). Kernel-density estimations (KDE) are mostly used for animal home range computation (Walter et al., 2011). In recent years, the Brownian bridge movement model (BBMM) has often been used on GPS trajectories to estimate home ranges, animal migration routes or movement patterns. BBMM offers an improvement over KDE because it considers transitions and the time between successive positions (Bullard, 1999; Farmer et al., 2010; Fischer, Walter & Avery, 2013; Horne et al., 2007; Sawyer et al., 2009; Takekawa et al., 2010). Using BBMM, Horne et al. (2007) introduced estimating probability density functions, or rather utilization distributions (UDs). The different probability levels of the UD give insight into how likely it is that an entity will stay in a certain area. Depending on the research interest, UDs can tell us about animal resource use, frequency of space use, dynamics of populations, or home ranges (Bullard, 1999; Horne et al., 2007).

From those ranges or areas, regular movement behaviour can be determined, e.g. where and when an entity regularly spends time. Moreover, deviations from regular whereabouts ranges can be detected. In animal movement ecology, for example, the estimation of migration routes can be extended to predict the usual return of the animals in the summer or winter season. So far, BBMM has been used mostly on animal movement data, but we investigated whether the model would also be of interest for human movement behaviour analysis to estimate human whereabouts ranges, complementing the time-based and density-based clustering methods already used to address this task (Ashbrook & Starner, 2003; Castelli et al., 2007; Hightower et al., 2005; Kang et al., 2004). The existing approaches generate location clusters by identifying stay points from the GPS trajectory (Ye et al., 2009). A disadvantage of spatio-temporal clustering approaches is that they cannot attribute two different stays in the same place to one cluster; instead, this results in two individual clusters, or rather centroid points, being created (Kang et al., 2004; Ye et al., 2009). With the approach presented in this paper, the process is reversed: activity areas belonging to one regularity class are estimated by using location clusters. The location clusters are the whereabouts ranges obtained from BBMM to determine frequently visited places (Horne et al., 2007). By establishing a user's regular movement behaviour from those whereabouts ranges, alerts could be triggered when unusual behaviour is recognized (Castelli et al., 2007). For instance, assistive systems for people with cognitive impairments could be implemented to compensate for those deficits (Hort et al., 2007).

In this paper, we aim to answer the following questions:

- How does BBMM perform with respect to quality and computational costs for modelling human movement data in order to detect regularities?
  Applying BBMM to large datasets of movement points leads to very long processing times. To reduce processing times, the BBMM was applied to daily, high-sampled GPS trajectories of humans. In order to obtain a ground truth data set, the trajectories and trip protocols of two individuals were recorded. The

resulting probability surfaces for the seven days of the week were merged to obtain the seven reference whereabouts ranges (Monday to Sunday). These merged activity ranges were then used to determine regularities in human movement behaviour: the trajectories were intersected with the corresponding BBMM's whereabouts ranges to create whereabouts areas and whereabouts tables (see step 3 in section 2.1 below, and Figure 1) describing stays of at least 15 minutes. We investigated how resulting whereabouts areas model the whereabouts of the person, particularly in urban environments. As explained in detail in section 2.3, the spatial accuracy and the uniqueness of the resulting whereabouts areas were assessed by calculating the distance between the tagged locations and the centroids of the whereabouts areas, i.e. we measured how well the tagged locations were recognized by the enhanced BBMM. The method allows the detection of further regularities, and the more accurate the area calculated the better the actual regularity can be determined.




| Centroid longitude | Centroid latitude | Entry time | Exit time | Stay duration [min] |
|---|---|---|---|---|
| 13.0409 | 47.8224 | 2011-01-01 15:30 | 2011-01-01 16:00 | 30 |
| 13.0409 | 47.8224 | 2011-01-01 16:30 | 2011-01-01 16:45 | 15 |

**Figure 1:** Model of trajectory intersection with whereabouts area (shown as a polygon), and corresponding whereabouts table

If the real-time use of the method with mobile devices is considered, then a second research question arises:

- Can we reduce computational costs of BBMM by simply down-sampling the existing data?
  For comparative purposes, data was down-sampled from 3 to 60 seconds in order to reduce the number of track points to assess the possible real-time application of the approach. For this, a comparison of the spatial quality for the 3-second and the 60-second samplings was carried out (see section 3.2).

Whereas Brownian bridges have been used for human GPS data (Lin & Hsu, 2014), as far as we know BBMM has not yet been applied to human movements. Section 2 describes the proposed BBMM adaptation and introduces the spatial quality measures. In Section 3, empirical results are discussed. Finally, the conclusions of our work are provided.

# 2 Brownian Bridge-based Approach

## Brownian Bridge-based Regularity Extraction

**Step 1** (Figure 2): GPS trajectories are preprocessed before BBMM is applied to them. All trajectories are cleaned of common data errors, such as redundant GPS points, outliers or points with identical coordinates (smooth & filter). The result of applying BBMM to GPS trajectory data is a utilization distribution (UD) which describes the whereabouts ranges by way of probabilities. For UD estimation, it is necessary to split at midnight and merge the trajectories so that each trajectory belongs only to one regularity class. Regularities that are grouped by days (i.e. weekdays as cycle classes) are of interest. Hence, the recorded trajectories are split and merged into one trajectory for each observed day (split & merge).

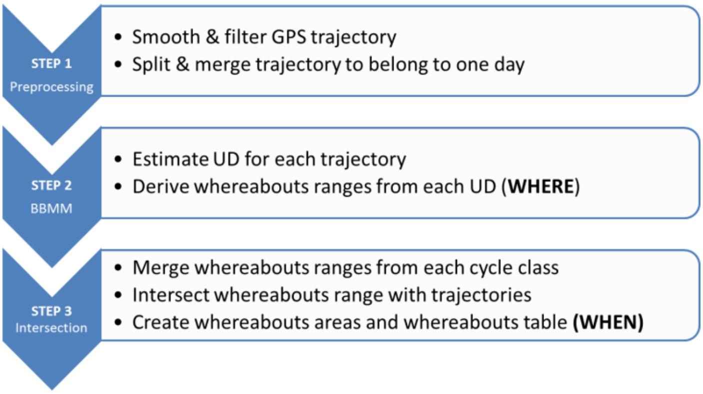



**Figure 2:** Brownian bridge-based regularity extraction

**Step 2:** BBMM estimates the probability of staying in a specific area based on the knowledge of space and time distance between any two successive positions of a recorded movement path. BBMM is a kernel method and considers timestamps of measured positions, e.g. GPS measurement on the earth's surface. To estimate BBMM probability density function from trajectories, BBMM uses a random walk, or rather Brownian bridge, to describe the probability of staying at a certain place at a certain time between successive GPS observations (Horne et al., 2007). The model considers the Brownian motion variance (BMV) parameter $\sigma_m^2$ which is related to an entity's speed and direction and mirrors the variance of the random walk between any two successive positions. The BMV is estimated by using a maximum likelihood approach (Horne et al., 2007) based on the empirical data (Section 2.2). Furthermore, the incorporated location error $\delta^2$ reflects the circular normally-distributed uncertainty in the positions (Horne et al., 2007). A 95% Horizontal Error of 9 metres is used for the Global Average Position Domain Accuracy (WJH Technical Center, 2014) because of a missing independent estimate for our data. The result of applying BBMM on GPS trajectory data is a UD which describes whereabouts ranges by the use of probabilities. This discrete bivariate probability density function is interpreted as a two-dimensional relative frequency distribution for an entity's positions over an observed period of time (Van Winkle, 1975). The combination of spatial and temporal information provides precise estimates of space use (Byrne et al., 2014). The model estimates the UD for cells of a grid superimposed on the positions describing the probability of staying in each grid cell over the entire observation time (Horne et al., 2007).

After applying BBMM to each trajectory separately, the result is a set of UDs. Each UD estimates the probability p of which area A the person P stayed in on day d. The whereabouts ranges are derived from the UDs and describe the minimum area A in the UD space for which the relocation probability p of a person P is equal to a specified value v. We are looking for that v which defines the whereabouts ranges, so that they represent the places where the person stayed longest during that day. A whereabouts range can be defined as an estimated minimum area on which the relocation probability of a person is equal to a specified value. For example, in animal ecology, 50% and 95% BBMMs are commonly used to describe the core area of use and the standard home range size, respectively (Fischer et al., 2013). Therefore, whereabouts ranges are derived from UDs with probabilities from 50% to 95% in steps of 5%, i.e. to estimate those ranges in which the relocation probability of a person is between 50% and 95% for that day.

**Step 3:**The daily whereabouts ranges of one probability level are fitted to one reference whereabouts range for each weekday, which is called a whereabouts area. The resulting whereabouts areas describe the merged ranges over the same weekday of a person's particular relocation probability. Probability levels between 50% and 95% are evaluated to find the percentage level which best suits the task of determining whereabouts areas for the ground truth data (Section 2.2). Spatial quality measures are used in order to compare ground truth with the resulting whereabouts areas. The UD does not include time or regularity information about when and how long a person stays where. To extract the additional information, the boundaries of the whereabouts areas are intersected with the corresponding trajectories to produce a person's whereabouts table.

During the intersection process, the whereabouts areas are modified. These areas are formed by polygons of the whereabouts range in which, according to our ground truth data, a person stayed at least 15 minutes, intersecting with trajectories. The first and last points of the trajectory within the polygon are the entry and exit points, with start and end timestamps (Figure 1). The timestamps are used to obtain the stay duration within the area. The centroids of the polygons obtained are used as detected place positions for the quality evaluation and to assess the probability level v.

Additionally, the minimum stay duration criterion is applied to each of the resulting intersection points in the table. If the stay duration at the intersection lasts less than 15 minutes, the entry is removed from the table. The results are whereabouts tables containing spatial information (centroids of polygons) and time information (stay durations within the polygons with corresponding timestamps). Hence, it is possible to reconstruct when a person stayed in a certain area and on which day. Using this table, the regularities can be computed easily by counting different places visited for a specific daytime interval.

For detailed explanation of BBMM and UD, we refer to Horne et al. (2007). For calculation, the adehabitatHR package was used (Calenge, 2006), with the R version 3.2.0 (R Core Team, 2015). The package includes the Brownian bridge kernel method to estimate animal home ranges, and uses a square-cell grid on which the UD is estimated. The side length of cells is obtained from the empirical data (Section 2.2). R is a free software environment for statistical computing and graphics.[1]

## Ground truth data

To obtain a trajectory data set that has ground truth, two people recorded their daily life using GPS devices. They logged every stay with arrival and departure times and documented each stay ≥ 15 minutes in a trip protocol. The locations and times included in the protocol serve as the validation data for the model. Person A recorded using a QSTARZ GPS Travel Recorder BT-Q1000XT; person B used a QSTARZ GPS Data Recorder CR-Q1100P. In order to ensure appropriate data quality, a sampling rate of 3 seconds was used (Schneider et al., 2015). To ensure that all places were tagged in identical fashion, the people involved in the test provided the Open Street Map (OSM)2 features (mostly buildings) of their whereabouts. The centroids of each OSM feature were set as coordinates for the tagged places. The trip protocol created additionally includes reported modes of movement, such as walking, jogging, driving, motorcycling and cycling. This resulted in mean BMVs of (A) $\sigma_m^2 = 0.05$ and (B) $\sigma_m^2 = 1.7$. Trajectories of over 150 km were excluded because unusual behaviours like air travel or longer journeys were not included in our whereabouts range estimation.

Person A tagged 25 places and travelled 587.7 km in total; person B tagged 36 places and covered 460.4 km. This yielded 39 recorded and reported daily trajectories for A, and 38 for B. The BBMM was applied to the trajectories split and merged of actual observation days.

A square-cell grid was created and used to estimate the UD for each cell (see step 2 in Section 2.1). The side length of one cell (53 m) was calculated by averaging the sum of the square root of the area of each tagged place (35 metres) and adding twice a location error of 9 metres (WJH Technical Center, 2014). The UD estimation of the BBMM is applied to 53 x 53 m cell grids. For each trajectory, a different grid is computed.

For a preliminary assessment of the computational costs of BBMM, the shortest (480 m) and longest (85.9 km) trajectories were compared. In terms of processing times (Lenovo T450s, i7-5600U 2.6 GHz, 12 GB RAM), this means a time range between 2 seconds and 7.2 hours. After down-sampling the trajectories from 3 seconds to 60 seconds, the processing time decreases to 150 milliseconds and 59.8 minutes.

## Quality evaluation

The objective of the quality evaluation is to assess the spatial quality performance of the approach. Therefore, two measures are introduced: Qsa computes the accuracy of the spatial detections, and Qsu the uniqueness of the detected places. For both measures, the maximum

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1 http://www.r-project.org

2 https://www.openstreetmap.org/copyright

value is 1 and the minimum value is 0. The ground truth data presented in Section 2.2 is used as input data for the model; the trip protocols of persons A and B are the validation data.

**Spatial accuracy**

In this context, spatial accuracy relates to the distances between tagged places (ground truth) and detected places (centroids from the whereabouts area), and the number of detected places. There are T tagged places and P detected places. Around each tagged place, a circular buffer with a radius $r = 53$ metres is created, which is the same length as the grid cell side length used for the BBMM.

For a detected place to be assigned to a tagged place, the Euclidian distance between the tagged place $P_t$ and the detected place $P_p$ must be less than or equal to r. A distance matrix with elements $d_{t,p}$ is obtained for which $d_{t,p}$ equals zero if the Euclidian distance between tagged and assigned detected places is greater than r.

$$\left\|P_p - P_t\right\|_2 := \sqrt{(x_p - x_t)^2 + (y_p - y_t)^2}$$

$$d_{t,p} := \begin{cases} \left\|P_p - P_t\right\|_2, & for \left\|P_p - P_t\right\|_2 \leq r \\ 0, & otherwise \end{cases}$$

Next, the mean of the distances for each tagged place is computed:

$$\bar{d}_t := \frac{\sum_p^P d_{t,p}}{\sum_p^P sgn(d_{t,p})}$$

Then the degree of correctness of the detected places (denoted by $q_t$) for each tagged place is obtained. This value assesses how accurate the detection of the tagged place is. There are three cases: (1) as long as $\bar{d}_t \leq \frac{r}{2}$ is valid, the detected place is assumed to be correctly detected; (2) when $\frac{r}{2} < \bar{d}_t \leq r$, the mean distance is divided by r; (3) values equal to 1 indicate best recognition of the tagged place, while values equal to 0 indicate the worst recognition. In other words, the tagged place is not detected.

$$q_t := \begin{cases} 1 & if\ \bar{d}_t \leq \frac{r}{2} \\ 1 - \frac{\bar{d}_t}{r} & if\ \frac{r}{2} < \bar{d}_t \leq r \\ 0 & otherwise \end{cases}$$

$$Q_{sa} := \frac{\sum_t^T q_t}{T}$$

In the final step, values of $q_t$ are added and divided by the total number of tagged places T. Hence, $Q_{sa}$ shows the accuracy of the correctly-assigned detected places.

**Spatial uniqueness**

The uniqueness of a detected place assigned to a tagged place is shown by $Q_{su}$. This measure can be referred to as the uniqueness of recognizing tagged places, or rather of assigned detected places. It compares the number of detected places which are assigned to multiple tagged places $N_{multiple}$ to the total number of detected places P.

$$Q_{su} := 1 - \frac{N_{multiple}}{P}$$

The number of detected places assigned to tagged places $N_{assigned}$ is not to equal the number of tagged places, because one tagged place can be recognized by more than one detected place. The number of detected places assigned to tagged places is determined by

$$M := \frac{N_{assigned}}{P}$$

# 3 Empirical Results and Discussion

## Whereabouts modelling on original trajectories

**Percentage levels – step 2, whereabouts range estimation:** The number of detected places, spatial accuracy and uniqueness are computed for persons A and B for five percentage levels from 50% to 95% (Table 1). In general, the number of detected places rises with increasing probability due to the growing size of the investigated whereabouts areas. Higher probability levels (e.g. 85% for person B) may merge two or more polygons of the whereabouts area of the previous probability level (e.g. 80%), which slightly increases the number of detected places, for example from 70 to 74 detected places. In Figure 4, the 80% BBMM represented inherits five polygons, while the 85% BBMM provides two. The rising number of detected places for 95% BBMM is due to the many small stretched polygons along the trajectory. With 95% relocation probability, the transitions of persons A and B are considered; hence, the recognition of detected places is not useful. The highest spatial accuracy for person A is 0.306 for 80% BBMM, and for person B 0.273 for 85% BBMM. Comparing the number of the detected places and the spatial accuracy of persons A and B in scatterplots (see Figure 3), no certain percentage value can be determined to define a universal, valid, standard probability level. The range between 75% and 85% shows moderately promising results. On the other hand, the spatial uniqueness $Q_{su}$ is always 1, which means that the radius around each tagged place is sufficient to ensure the spatial uniqueness of a detected place. The whereabouts areas of a person, which are represented by polygons, show approximately where the person stays on a certain day. When comparing the number of detected places and measured areas of two whereabouts areas, e.g. Tuesday and

Sunday (Table 2), spatial differences between weekday and weekend whereabouts areas (thus a kind of regularity) emerge.

**Table 1:** Results of the probability level evaluation

| | Person A | | | | | Person B | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| **Whereabouts area** | **50%** | **75%** | **80%** | **85%** | **95%** | **50%** | **75%** | **80%** | **85%** | **95%** |
| Number of tagged places | 25 | 25 | 25 | 25 | 25 | 36 | 36 | 36 | 36 | 36 |
| Number of detected places | 2 | 74 | 142 | 289 | 783 | 25 | 44 | 70 | 74 | 404 |
| $M$ | 1.000 | 0.297 | 0.162 | 0.083 | 0.024 | 0.680 | 0.455 | 0.300 | 0.378 | 0.064 |
| $Q_{sa}$ | 0.004 | 0.294 | 0.306 | 0.289 | 0.199 | 0.189 | 0.214 | 0.234 | 0.273 | 0.216 |
| $Q_{su}$ | 1.000 | 1.000 | 1.000 | 1.000 | 1.000 | 1.000 | 1.000 | 1.000 | 1.000 | 1.000 |

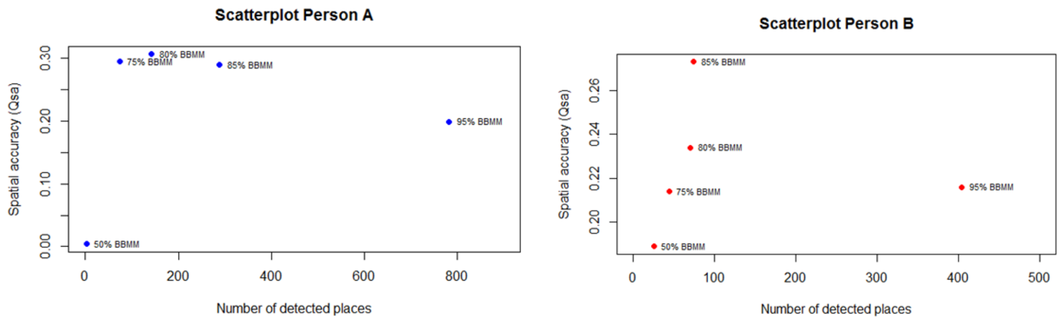



**Figure 3:** Scatterplots of spatial accuracy vs. number of detected places for persons A and B

**Table 2:** Comparison of Tuesday and Sunday whereabouts areas

| | | Tuesday | | | Sunday | | |
|---|---|---|---|---|---|---|---|
| | | 75% | 80% | 85% | 75% | 80% | 85% |
| Person A | #detected places | 7 | 9 | 9 | 28 | 74 | 153 |
| | Area [m²] | 5.2e⁴ | 6.9e⁴ | 8.9e⁴ | 8.5e⁴ | 25.4e⁴ | 97.1e⁴ |
| Person B | #detected places | 6 | 14 | 14 | 8 | 23 | 11 |
| | Area [m²] | 6.7e4 | 10.2e4 | 14.8e4 | 8.9e4 | 17.1e4 | 5.5e4 |

**Interpretation of recognition rate:** In Figures 4 and 5, 75%, 80% and 85% polygons for Tuesdays for person A ("home" and "work") and B ("home") are illustrated. The yellow dots mark tagged places from the ground truth data; the green, red and blue dots mark the detected places. The shapes of the polygons reflect the streets and areas in which the person moved, with some extension around these due to the random walk assumption, or rather BMV of the BBMM. Tagged places which are frequently used and in which the person stayed most of the total observed time (e.g. "home" or "work") are likely to be detected. Single short stays are not likely to be considered (e.g. visiting a grocery store).

**Regularities – step 3, whereabouts table creation:** From the whereabouts tables, we can reconstruct at what time a person was in a certain area by binning the intersected trajectories into 1 hour bins. For example, between 9 and 10 a.m. on Tuesday, person A was in the polygon m. Based on the frequency and the unique IDs of the polygons, the probability of where and when a person is likely to stay there is estimated. In Figure 6, the relative frequency over times of the day of staying in the polygon "home" on any Tuesday is presented.

Person B turned the GPS recorder off while spending time in buildings. After restarting the tracker, whether at the same place or at another, the intervening time is taken into account and random walk around the area is assumed. The resulting whereabouts area expands in a circular fashion because of the time supposedly spent in this area and the shape of the inherited functions of the BBMM. This is the reason why the spatial accuracy is so low (Table 1).

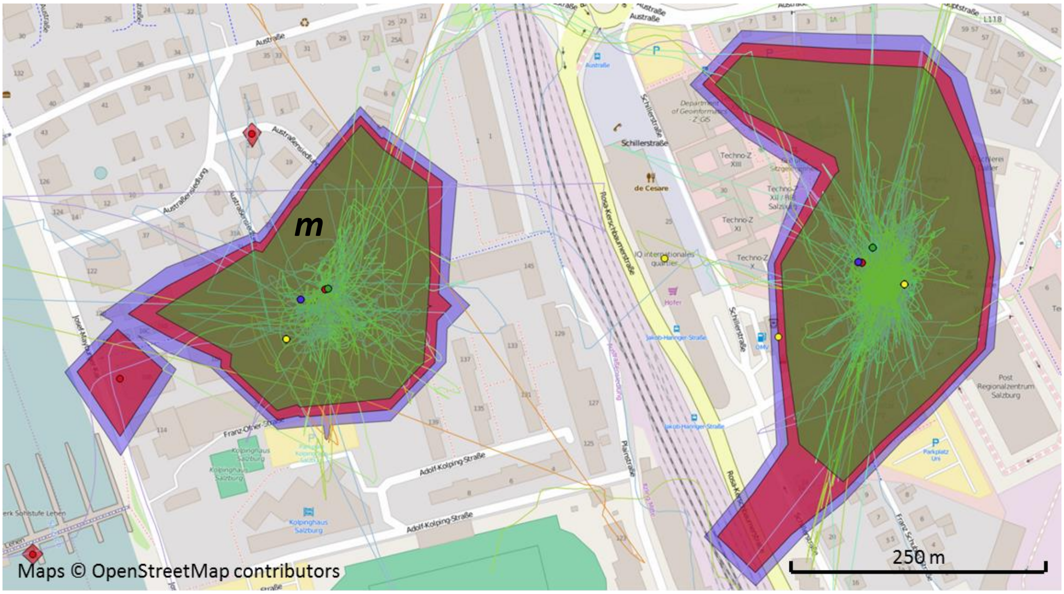
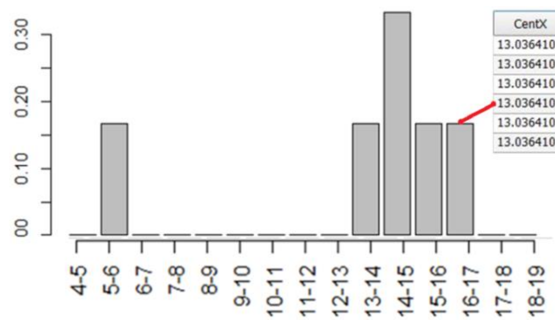



**Figure 4:** 75% (green), 80% (red), and 85% (blue) "home" and "work" polygons for Tuesday for person A, including tagged (yellow) and detected (green, red, blue) places, with polygon labelled m


**Figure 5:** 75% (green), 80% (red), and 85% (blue) "home" polygon for Tuesday for person B, with tagged (yellow) and detected (green, red, blue) places

Other interferences on the quality of the whereabouts range estimation relate to the quality of the GPS data. Although smoothing and filtering is performed, some issues remain, such as GPS tracker jump-starts or increased GPS error inside buildings. Using BBMM for movement behaviour modelling in urban environments requires sophisticated preprocessing, such as merging trajectories with additional artificial GPS points, and minimizing GPS error as far as possible.




| CentX | CentY | EnterTime | LeaveTime | PolysID |
|---|---|---|---|---|
| 13.036410234... | 47.822672290... | 2014-08-12 14:35:42 | 2014-08-12 15:21:12 | Tuesday |
| 13.036410234... | 47.822672290... | 2014-08-12 15:25:59 | 2014-08-12 15:42:15 | Tuesday |
| 13.036410234... | 47.822672290... | 2014-08-19 14:11:48 | 2014-08-19 14:29:29 | Tuesday |
| 13.036410234... | 47.822672290... | 2014-08-19 16:10:21 | 2014-08-19 16:46:47 | Tuesday |
| 13.036410234... | 47.822672290... | 2014-09-02 13:25:02 | 2014-09-02 13:45:49 | Tuesday |
| 13.036410234... | 47.822672290... | 2014-09-16 05:23:20 | 2014-09-16 05:46:41 | Tuesday |

**Figure 6:** Relative frequency over daytime bins for polygon m extracted from the whereabouts table of the 75% Tuesday whereabouts area for person A. Values overnight are missing because the tracker was turned off.

## Comparison with resampled trajectories

In order to ensure future implementation as a real-time application, efforts were made to improve the processing times by resampling trajectories and reducing sampling rates from high (3 seconds) to low (60 seconds) sampling rates. The effects of down-sampling on BBMM results can be seen by comparing the quality results and processing time of the 75% whereabouts area with those of the 80% whereabouts area (person A), and the 80% whereabouts area with those of the 85% whereabouts area (person B), shown in Table 3. The higher percentage levels (80% for person A; 85% for person B) were selected due to the highest spatial accuracy obtained (see Table 1). The second percentage levels (75% and 85%) were compared because their whereabouts areas are smaller and might increase the spatial accuracy.

Down-sampling the trajectory increases spatial accuracies except for person B's 85% area (Figure 7). For person B, the spatial accuracy measure of the 80% whereabouts area is higher than for the high-sampled trajectories, while M (i.e. the number of detected places assigned to tagged places) decreases due to an increase in the number of detected places. The quality of the correctly-assigned detected places is improved. This can be observed for person A as well. The number of detected places falls while $Q_{sa}$ increases slightly when resampling at a rate of 60 seconds. Unlike person B, for person A M shows a simultaneous increase of correctly-assigned detected places with an increase in spatial quality ($Q_{sa}$). 34% of the 68 detected places for the 75% area of person A are assigned to tagged places with spatial quality $Q_{sa}$= 0.37. None of the cases investigated achieve a spatial accuracy of more than 0.4.

Applying BBMM is computationally costly, particularly on 3-second sampled data. In Table 3, the average processing times for BBMM computations are listed. Down-sampling decreases the processing time rapidly. In Figure 8, the 75% area from the original trajectory (green) and from the down-sampled trajectory (orange) of person A is illustrated. Spatial accuracy increases. However, the whereabouts areas grow due to the assumption of random walking. The tagged places are inside the polygon but not close enough to the centre point (orange), which facilitates low $Q_{sa}$ measures. This can be an indicator that the quality measure $Q_{sa}$ is not adequately defined and that a redesign is needed.

**Table 3:** Comparison of 3- and 60-second resolved GPS data for persons A (75% and 80% areas) and B (80% and 85% areas)

| | **Person A** | | | | **Person B** | | | |
|---|---|---|---|---|---|---|---|---|
| Whereabouts area | 75% | | 80% | | 80% | | 85% | |
| Sampling rate | 3 sec | 60 sec | 3 sec | 60 sec | 3 sec | 60 sec | 3 sec | 60 sec |
| Number of days | 39 | 39 | 39 | 39 | 38 | 38 | 38 | 38 |
| Number of tagged places | 25 | 25 | 25 | 25 | 36 | 36 | 36 | 36 |
| Number of detected places | 74 | 68 | 142 | 97 | 70 | 96 | 74 | 133 |
| M | 0.30 | 0.34 | 0.16 | 0.21 | 0.30 | 0.18 | 0.38 | 0.10 |
| $Q_{sa}$ | 0.29 | 0.37 | 0.31 | 0.36 | 0.23 | 0.27 | 0.27 | 0.18 |
| $Q_{su}$ | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 |
| Mean processing time [min] | 66 | 3 | 66 | 3 | 39 | 3 ½ | 39 | 3 ½ |

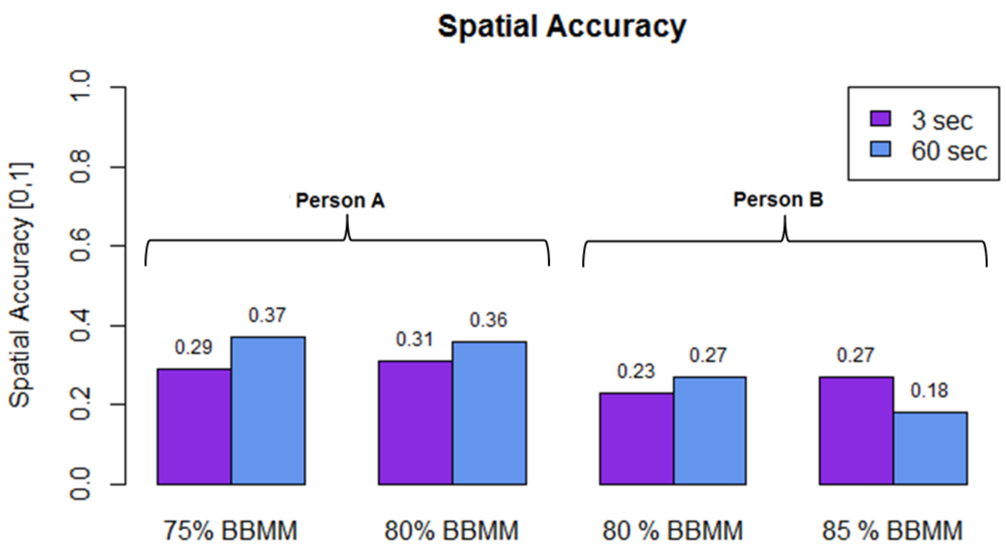



**Figure 7:** Comparison of spatial accuracies (Section 2.3) for persons A and B for 3- and 60-second sampling rates

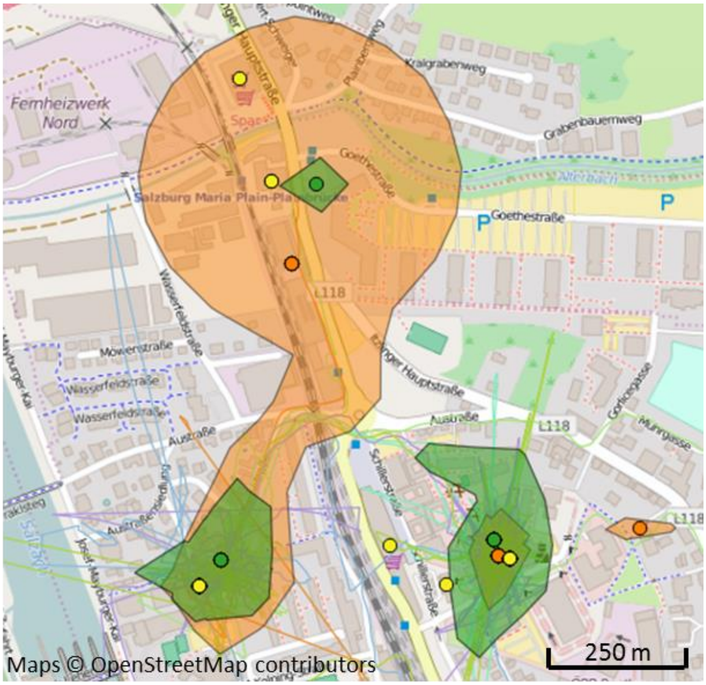



**Figure 8:** 75% polygons for Tuesday for person A using 60-second (orange) and 3-second (green) sampling rates, with corresponding detected places (orange, green) and tagged places (yellow)

# 4 Conclusions

Until now, BBMM has been used to answer questions in animal movement ecology, e.g. determining frequently used places. The method, inherently, cannot extract temporal information about used places. Hence, questions about "when and where" cannot be answered. The proposed enhancement of the BBMM approach modifies and intersects whereabouts ranges, derived from BBMM's utilization distributions, to gain further temporal information about when an entity stayed in a certain area for some time. The resulting whereabouts tables were used to determine regularities and probability distributions of stays for each polygon of the whereabouts areas. These regularities and the whereabouts areas could be used, for example, to support the independence of elderly people in their daily life or to get a deeper understanding of stay-move-stay regularities among animals.

The approach can model whereabouts areas but it is not useful for detecting certain limited stay points, such as single buildings. There are two reasons for this: firstly, close but different stays are merged together in one whereabouts range because BBMM does not distinguish between them. Secondly, inside a building GPS error increases and hence the GPS points spread around the building. Thus, spatial quality measures concerning the coordinates of just single centres are inappropriate. Comparing areas, e.g. shapes of buildings, would be a better approach – this maintains privacy, and knowledge about precise addresses is not usually important for scientific purposes.

Due to high processing times, the GPS trajectories were down-sampled from 3 to 60 seconds. Computational costs decreased and quality measures remained comparable to the high-sampling case. In order to identify points of stay, adaptations of spatio-temporal clustering methods could be considered and/or compared to our approach. The methods do not determine probabilities of whereabouts or regularities of when and where an entity stayed in certain areas, as our approach does. The evaluation showed that the spatial accuracy of the method should be improved. A down-sampling of GPS trajectories is one possible approach. Separating trajectories based on velocity, or evaluating a different merging technique to determine whereabouts areas might improve the results.

Nevertheless, the quality measures introduced can be used to assess the spatial quality of different detection methods and to fine-tune the modelling parameters for a specific application. Quality measures addressing the temporal accuracy of detected places could be developed. After all, the proposed BBMM adaptation is suitable to determine regularities of people's movement but it does not provide the expected precision to recognize single addresses.

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