Analysis of GOT Series

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exercise 4, part of the course cma (mainly based on Laube (2014))

Abstract

1 Input: Segmentation

You've read Laube and Purves (2011) about segmenting trajectories. In the paper, the authors define "*static*" fixes as "*those whose average Euclidean distance to other fixes inside a temporal window v is less than some threshold d*", as illustrated in Figure 1

a. Specify a temporal windows v for in which to measure Euclidean distances.

b. Measure the distance from every point to every other point within this temporal window v.

c. Remove "static points": These are points where the average distance is less than a given threshold. This segments the trajectory into subtrajectories.

d. Now remove short subtrajectories: These are trajectories with a short duration (whereas "short" is tbd).

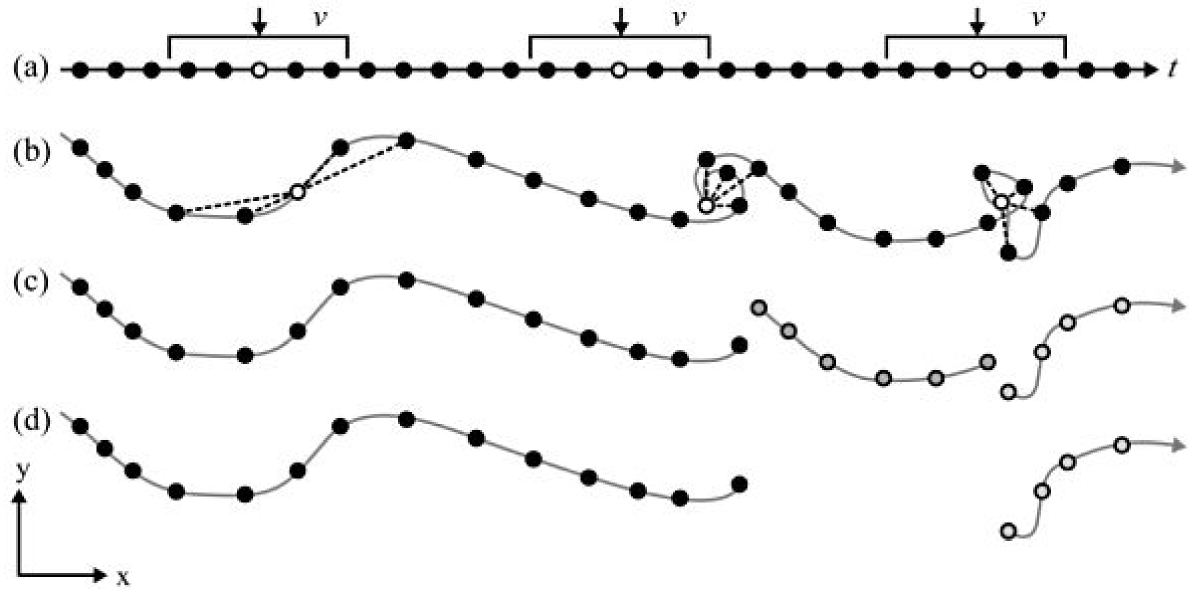

Figure 1: The figure from Laube and Purves (2011) visualizes steps a) zu d), which will be explained below

We will **demonstrate** implementing this method on the wild boar “Sabi”, restricting ourselves to a couple of tracking days. Your task will be to understand this implementation and apply it to your own movement data.

Open a RStudio Project for this week. Next, copy the wild boar data you downloaded last week (*wildschwein_BE_2056.csv*) to your project folder. If you cannot find this dataset on your computer, you can re-download it from moodle. Transform the data into an `sf` object, filter for the wild boar Sabi and a datetime between “2015-07-01” and “2015-07-03”.

```
pacman::p_load("readr", "sf","dplyr", "ggplot2")

wildschwein <- read_delim("data/wildschwein_BE_2056.csv", ",")
```

```
Rows: 51246 Columns: 6
-- Column specification --------------------------------------------------------
Delimiter: ","
chr  (2): TierID, TierName
dbl  (3): CollarID, E, N
dttm (1): DatetimeUTC

i Use `spec()` to retrieve the full column specification for this data.
i Specify the column types or set `show_col_types = FALSE` to quiet this message.
```

```r
# Careful! What Timezone is assumed?
sabi <- wildschwein |>
    st_as_sf(coords = c("E", "N"), crs = 2056, remove = FALSE) |>
    filter(
      TierName == "Sabi",
      DatetimeUTC >= "2015-07-01",
      DatetimeUTC < "2015-07-03"
      )

sabi |> summary()
```

```
    TierID            TierName            CollarID    
 Length:192         Length:192         Min.   :12275  
 Class :character   Class :character   1st Qu.:12275  
 Mode  :character   Mode  :character   Median :12275  
                                       Mean   :12275  
                                       3rd Qu.:12275  
                                       Max.   :12275  
  DatetimeUTC                          E                 N          
 Min.   :2015-06-30 22:00:13.00   Min.   :2569724   Min.   :1204916  
 1st Qu.:2015-07-01 09:56:28.50   1st Qu.:2569791   1st Qu.:1205121  
 Median :2015-07-01 21:52:58.50   Median :2570466   Median :1205140  
 Mean   :2015-07-01 21:52:50.82   Mean   :2570242   Mean   :1205172  
 3rd Qu.:2015-07-02 09:49:05.75   3rd Qu.:2570475   3rd Qu.:1205180  
 Max.   :2015-07-02 21:45:16.00   Max.   :2570927   Max.   :1205957  
          geometry  
 POINT        :192  
 epsg:2056    :  0  
 +proj=some...:  0  
```

```r
sabi |> str()
```

```
sf [192 x 7] (S3: sf/spec_tbl_df/tbl_df/tbl/data.frame)
 $ TierID     : chr [1:192] "002A" "002A" "002A" "002A" ...
 $ TierName   : chr [1:192] "Sabi" "Sabi" "Sabi" "Sabi" ...
 $ CollarID   : num [1:192] 12275 12275 12275 12275 12275 ...
 $ DatetimeUTC: POSIXct[1:192], format: "2015-06-30 22:00:13" "2015-06-30 22:16:06" ...
 $ E          : num [1:192] 2569972 2569975 2570266 2570208 2570247 ...
```

```
 $ N          : num [1:192] 1205366 1205637 1205857 1205913 1205731 ...
 $ geometry   :sfc_POINT of length 192; first list element:  'XY' num [1:2] 2569972 1205366
 - attr(*, "spec")=
  .. cols(
  ..   TierID = col_character(),
  ..   TierName = col_character(),
  ..   CollarID = col_double(),
  ..   DatetimeUTC = col_datetime(format = ""),
  ..   E = col_double(),
  ..   N = col_double()
  .. )
 - attr(*, "problems")=<externalptr>
 - attr(*, "sf_column")= chr "geometry"
 - attr(*, "agr")= Factor w/ 3 levels "constant","aggregate",..: NA NA NA NA NA NA
  ..- attr(*, "names")= chr [1:6] "TierID" "TierName" "CollarID" "DatetimeUTC" ...
```

```
sabi |>
  ggplot(aes(E,N)) +
  geom_point() +
  geom_path() +
  theme_minimal()
```

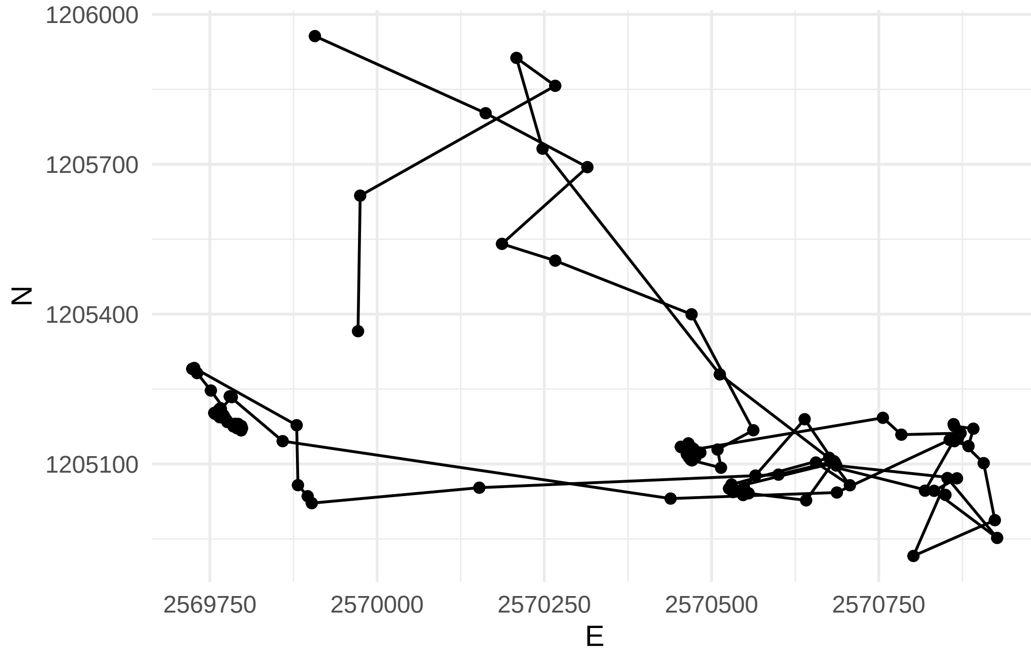

Figure 2: Movement of the wild boar 'Sabi' in the timespan 01 - 02.07.2015. The cluster of dots / fixes are possible 'static' points

Step a): Specify a temporal window v

In the above dataset, the sampling interval is 15 minutes. If we take a temporal window of 60 minutes, that would mean including 4 fixes. We need to calculate the following Euclidean distances (pos representing single location):

1. `pos[n-2]` to `pos[n]`
2. `pos[n-1]` to `pos[n]`
3. `pos[n]` to `pos[n+1]`
4. `pos[n]` to `pos[n+2]`

Step b): Measure the distance to every point within v

We can use the function distance_by_element from week 2 in combination with `lead()` and `lag()` to calculate the Euclidean distance. For example, to create the necessary offset of n-2, we use `lag(x, 2)`. For each offset, we create one individual column.

```
distance_by_element <- function(later, now) {
  as.numeric(
    st_distance(later, now, by_element = TRUE)
  )
```

```r
}



sabi <- sabi |>
  mutate(
    nMinus2 = distance_by_element(lag(geometry,2),geometry),
    nMinus1 = distance_by_element(lag(geometry,1),geometry),
    nPlus1 = distance_by_element(geometry,lead(geometry,1)),
    nPlus2 = distance_by_element(geometry,lead(geometry,2))
  )
```

Now we want to calculate the mean distance of `nMinus2`, `nMinus1`, `nPlus1`, `nPlus2` for each row. Since we want the mean value *per Row*, we have to explicitly specify this before `mutate()` with the function `rowwise()`. To remove this rowwise-grouping, we end the operation with `ungroup()`.

Note that for the first two positions, we cannot calculate a `stepMean` since there is no Position `n-2` for these positions. This is also true for the last to positions (lacking a position `n+2`).

```r
sabi <- sabi |>
    rowwise() |>
    mutate(
        stepMean = mean(c(nMinus2, nMinus1, nPlus1, nPlus2))
    ) |>
    ungroup()
```

Step c): Remove "static points"

We can now determine if an animal is moving or not by specifying a threshold distance on `stepMean`. In our example, we use the mean value as a threshold: Positions with distances below this value are considered static.

```r
sabi <- sabi |>
    mutate(static = stepMean < mean(stepMean, na.rm = TRUE))

sabi_moving <- sabi |>
    filter(!static)

sabi_static <- sabi |>
    filter(static)
```

```
sabi_moving |>
    ggplot(aes(E, N)) +
    geom_point(data = sabi_static, col = "red") +
    geom_path() +
    geom_point() +
    coord_fixed() +
    theme(legend.position = "bottom")
```

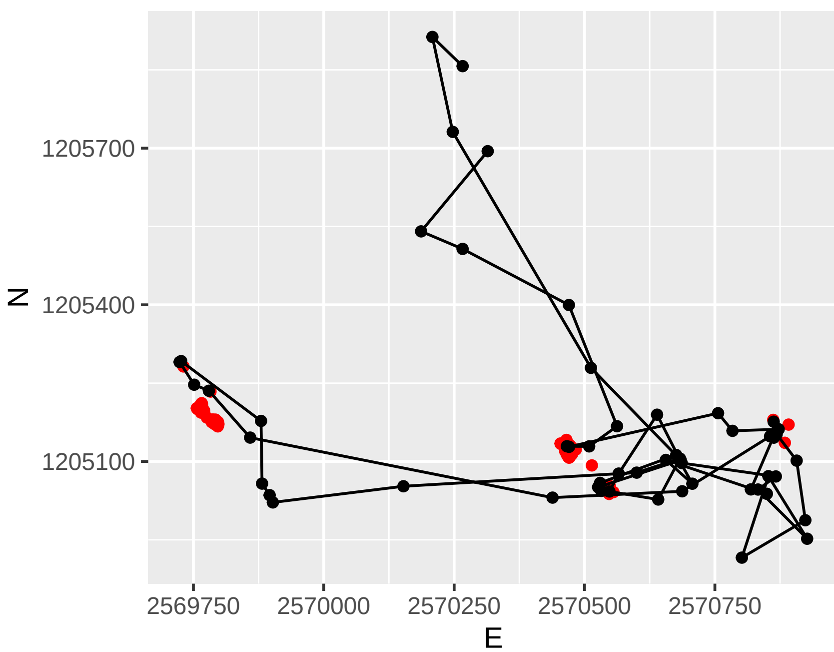

Figure 3: The trajectory of sabi. Red dots are static points, the black dots signify moving points

2 Exercise A: Segmentation

With the skills from Input: Segmentation you can now implement the segmentation algorithm described in Laube and Purves (2011) to either your own movement data or to a different wild boar using different sampling intervals.

2.1 Task 1: Calculate distances

Now, you can Step a): Specify a temporal window v and Step b): Measure the distance to every point within v, which you had used with sabi, on on your own movement data or to a different wild boar using different sampling intervals.

```
df_tannenhaeher <- read_delim("tannenhaeher.csv") |>
    st_as_sf(coords = c("x", "y"), crs = 2056, remove = FALSE)
```

```
Rows: 8721 Columns: 17
-- Column specification --------------------------------------------------------
Delimiter: ","
chr  (5): tag_tech_s, sensor_typ, individual, ind_ident, study_name
dbl  (9): long, lat, external_t, hdop, satellite_, height, tag_ident, x, y
lgl  (2): date, time
dttm (1): timestamp

i Use `spec()` to retrieve the full column specification for this data.
i Specify the column types or set `show_col_types = FALSE` to quiet this message.
```

```
df_tannenhaeher_K125864 <- df_tannenhaeher |>
  filter(ind_ident=="K125864")

df_tannenhaeher_K121752 <- df_tannenhaeher |>
  filter(ind_ident=="K121752")
```

```
df_tannenhaeher_K125864 |>
  ggplot(aes(x,y)) +
  geom_point() +
  geom_path(alpha=0.4) +
  theme_minimal()
```

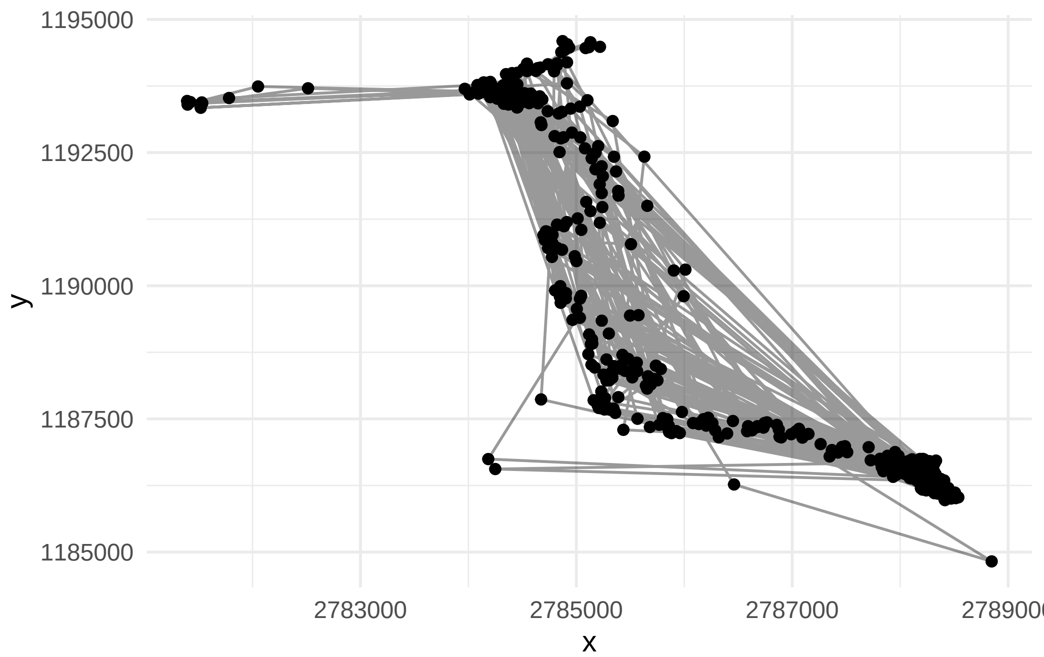

Figure 4: Movement of the Spotted Nutcracker K125864. The cluster of dots / fixes are possible 'static' points

```
steps <- function(df) {
  df_updated <- df |>
  mutate(
    nMinus2 = distance_by_element(lag(geometry,2),geometry),
    nMinus1 = distance_by_element(lag(geometry,1),geometry),
    nPlus1 = distance_by_element(geometry,lead(geometry,1)),
    nPlus2 = distance_by_element(geometry,lead(geometry,2))
  ) |>
    rowwise() |>
    mutate(
        stepMean = mean(c(nMinus2, nMinus1, nPlus1, nPlus2))
    ) |>
    ungroup()|>
    mutate(static = stepMean < mean(stepMean, na.rm = TRUE))

  return (df_updated)
}


df_tannenhaeher_K125864 <- df_tannenhaeher_K125864 |> steps()
```

```
df_tannenhaeher_K121752 <- df_tannenhaeher_K121752 |> steps()
```

```
df_tannenhaeher_K125864|>
  filter(!static) |>
    ggplot(aes(x, y)) +
    geom_path(alpha=0.3) +
    geom_point() +
    geom_point(data = df_tannenhaeher_K125864 |> filter(static), col = "red") +
    coord_fixed() +
  theme_minimal()
```

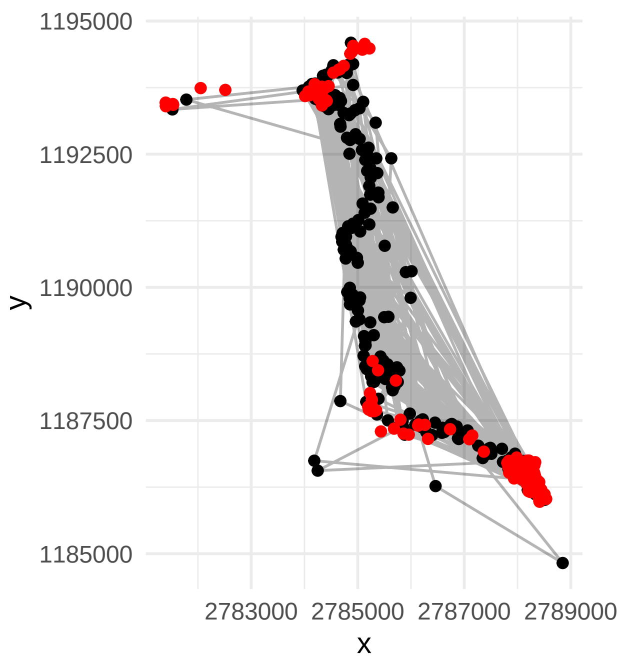

Figure 5: The trajectory of Spotted Nutcracker K125864. Red dots are static points, the black dots signify moving points

```
df_tannenhaeher_K121752|>
  filter(!static) |>
    ggplot(aes(x, y)) +
    geom_path(alpha=0.3) +
    geom_point() +
    geom_point(data = df_tannenhaeher_K121752 |> filter(static), col = "blue") +
    coord_fixed() +
  theme_minimal()
```

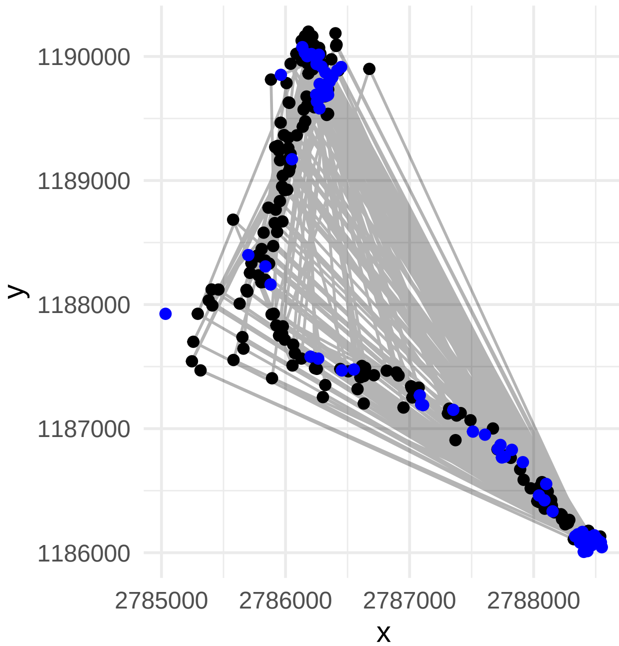

Figure 6: The trajectory of Spotted Nutcracker K121752. Blue dots are static points, the black dots signify moving points

3 References

Laube, Patrick. 2014. *Computational Movement Analysis*. 2014th ed. SpringerBriefs in Computer Science. Cham: Springer International Publishing AG.