Statistical Modeling of Animal Movement with R Package smam

Among the many R packages for animal movement (Joo et al. 2020), `smam` (Hu, Pozdnyakov, and Yan 2020) is unique in that it allows an animal to stay still instead of perpetual movement. This model is known as the moving-resting process, in which the holding times in the moving stage and the resting stage are exponentially distributed, and the moving stage is modeled by a Brownian motion. The model was first proposed in 2014 (Yan et al. 2014), but the measurement errors from the telemetric or GPS devices are not satisfactorily handled until our recent paper in Methods in Ecology and Evolution (Hu et al. 2021), which presents a solid and practical inference process for the moving-resting model with measurement errors (MRME).

Fitting the MRME model to animal movement data

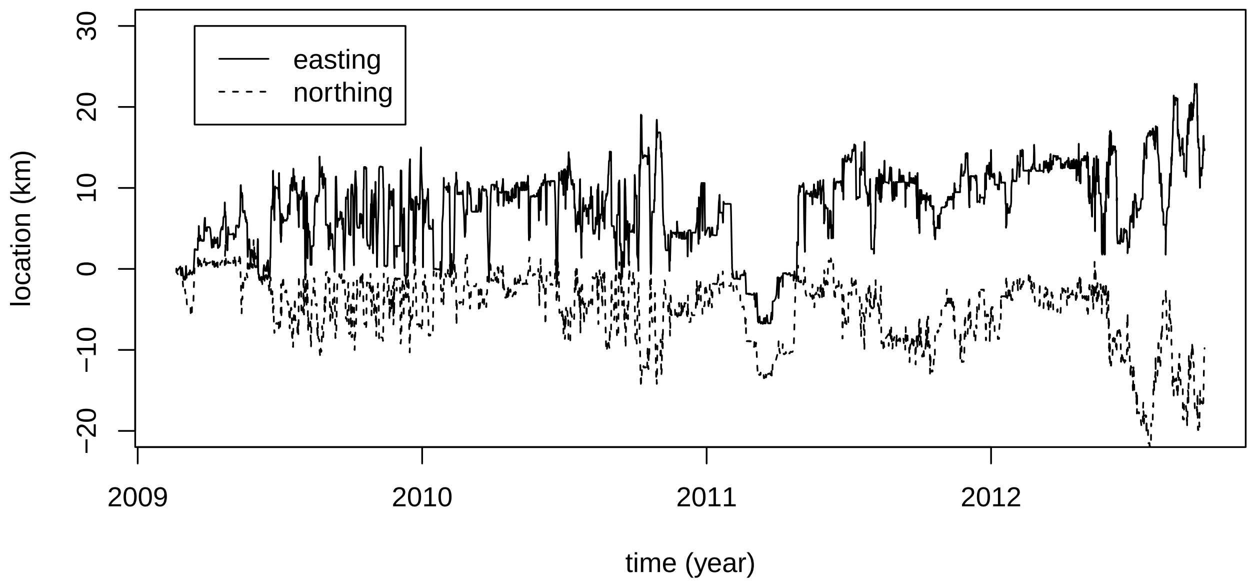
As an illustration, consider the movement data of a female mountain lion with id `f109` in the Gros Ventre Mountain area, Wyoming. This data set was analyzed in Hu et al. (2021). First, we need to load the package and GPS location data `f109raw`. The datasets analyzed by this package should be formatted as a `data.frame` whose first column is the observation time and the other columns are location coordinates. In `f109`, column `t` is the time of records collected in seconds, and columns `dE` and `dN` are the centered Universal Transverse Mercator (UTM) easting and northing in meters. The trace of this animal is shown in the following plot. The distance should be expressed in kilometers before analysis and plotting.

```
library(smam)
head(f109raw)
```

```
##          t   dE    dN
## 1 2009.136   18   -66
## 2 2009.136   10   -78
## 3 2009.136   30  -213
## 4 2009.136 -381  -383
## 5 2009.150  305 -1133
## 6 2009.153 -793  -307
```

```
## converting the distance units to kilometers
f109raw <- within(f109raw, {dE = dE / 1000; dN = dN / 1000})
```

```r
with(f109raw, plot(t, dE, type = 'l', ylim = c(-20, 30),
                   xlab = "time (year)", ylab = "location (km)"))
with(f109raw, lines(t, dN, lty = 2))
legend(2009.2, 30, c("easting", "northing"), lty = c(1, 2))
```



The mountain lions behave differently in summer and winter seasons. As a result, these two seasons have to be modeled differently. The summer is defined as June, July, and August. The winter is defined as December, January, and February We covert time units from years to hours for ease of interpretation of the Brownian motion mobility parameter.

```r
## define season
f109raw$season <- with(f109raw, {
    tt  <- t %% 1
    ifelse(tt > 5/12 & tt <= 8/12, "summer",
           ifelse(tt > 11/12 | tt <= 2/12, "winter", "other"))
})

## define time in hours
f109raw$hr <- (f109raw$t - 2009) * 365.25 * 24
## define year with March as starting month
f109raw$year <- (f109raw$t - 2/12) %/% 1

## subset of 2012 summer
summer2012 <- subset(f109raw, season == "summer" & year == 2012,
                     select = c("hr", "dE", "dN"))

## subset of 2011-2012 winter
winter2011 <- subset(f109raw, season == "winter" & year == 2011,
                     select = c("hr", "dE", "dN"))
```

```r
head(summer2012)
```

```
##            hr     dE      dN
## 3372 29953.53 16.534 -11.169
## 3373 29958.48 12.849  -8.064
## 3374 29962.49 17.007 -11.698
## 3375 29967.47 16.862 -11.779
## 3376 29972.51 17.059 -11.716
## 3377 29977.46 16.876 -11.404
```

```r
head(winter2011)
```

```
##            hr     dE     dN
## 2493 25568.67 14.280 -8.294
## 2494 25569.19 14.251 -8.341
## 2495 25569.69 13.740 -8.347
## 2496 25570.22 14.278 -8.278
## 2497 25573.51 14.268 -8.427
## 2498 25577.54 12.943 -7.845
```

Now, the MRME model can be applied. The estimation results are displayed in the following order:

- λ_M, rate parameter of the exponential holding time of moving;
- λ_R, rate parameter of the exponential holding time of resting;
- σ, mobility parameter of the Brownian motion in moving;
- σ_ϵ, standard error of the measurement error.

```r
## fit 2012 summer data to the MRME model
## This takes a while
fit_summer <- fitMRME(summer2012,
                      start = c(4, 0.4, 1, 0.05))
estimate(fit_summer)
#       lamM       lamR      sigma    sig_err
# 2.84049099 0.17869261 1.33492477 0.01852022

## fit 2011 winter data to the MRME model
fit_winter <- fitMRME(winter2011,
                      start = c(4, 0.4, 1, 0.05))
estimate(fit_winter)
#        lamM        lamR       sigma     sig_err
# 6.304029786 0.118513328 1.530265318 0.009068519
```

We use summer estimators as an example. The estimates $\hat{\lambda_M} = 2.84hr^{-1}$ and $\hat{\lambda_R} = 0.18hr^{-1}$ mean that the average durations of moving and resting are $1/2.84 = 0.35$ and $1/0.18 = 5.56$ hours. The estimate $\hat{\sigma} = 1.33km/hr^{1/2}$ tells us that if the lion keeps moving without stopping for one hour, the average departure from original point is $1.33km$. The last parameter estimate, $\hat{\sigma_\epsilon} = 0.019km$, is the standard error of the measurement error.

The package provides standard errors for inferences based on Godambe information and parametric bootstrap. The
recommended method is a parametric bootstrap, where `nBS` specifies the number of bootstraps, and `numThreads` specifies the number of threads to be used for multicore computers. The following code provides the estimated covariance matrix of estimators. Taking square root of diagonal elements gives us
the standard errors of the estimators.

```
vcov(fit_summer, nBS = 100, numThreads = 6)
#  |==========================================| 100%
#                [,1]          [,2]          [,3]          [,4]
# [1,]  2.111367e-01  1.483937e-03  3.629777e-02 -6.775386e-05
# [2,]  1.483937e-03  1.963202e-04 -2.547285e-05 -2.106885e-06
# [3,]  3.629777e-02 -2.547285e-05  1.127234e-02 -1.014327e-05
# [4,] -6.775386e-05 -2.106885e-06 -1.014327e-05  7.556806e-07
```

Summer data over multiple years can be pooled to form a more precise estimation.

```
## define summer batch variable
summer <- subset(f109raw, season == "summer",
                 select = c("hr", "dE", "dN", "year"))
```

Now, to fit the MRME model to only summer part of the dataset one should proceed as follow. The additional argument `segment="year"` identifies which observations are in the same year; the composite loglikelihoods for different years are added up as the pooled composite loglikelihood.

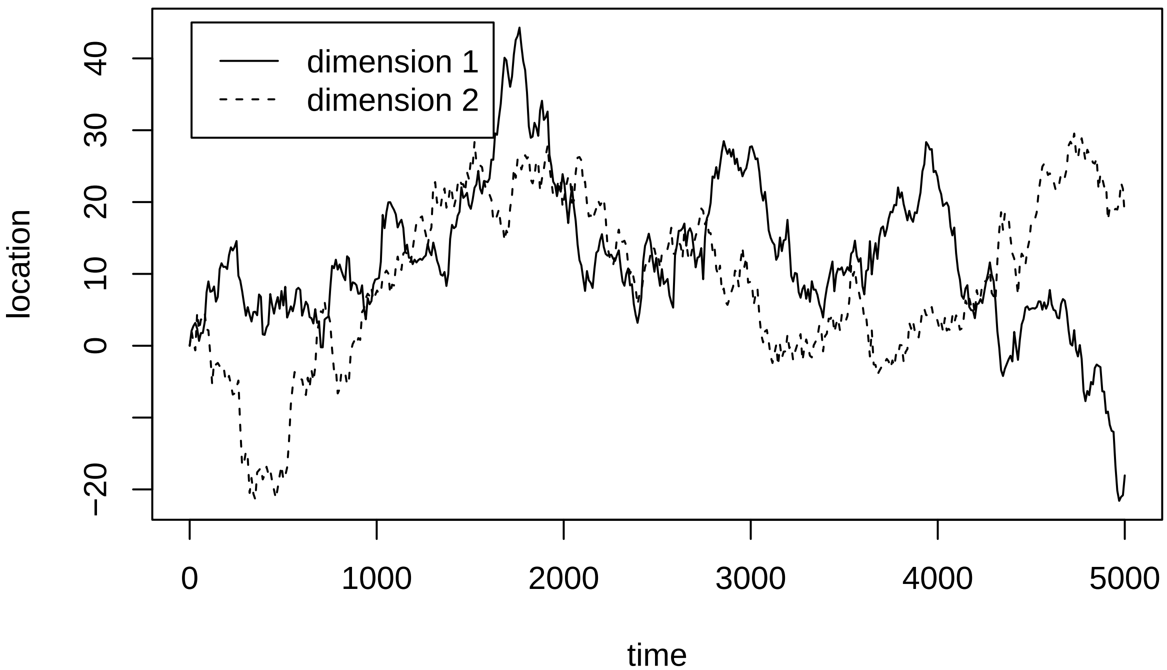
```
fit <- fitMRME(summer, start = c(5, 0.5, 1, 0.01),
               segment = "year")
estimate(fit)
#       lamM       lamR      sigma    sig_err
# 3.82490120 0.16065612 1.86454989 0.02043802
```

Simulation from for the MRME model

One might also want to generate movement data from the MRME model for exploration or simulation purposes. In the following example, we show how to generate a two-dimensional dataset from MRME model by R function `rMRME`. Here, we use `time` to indicates time points at which observations are to be simulated. Again, `lamM`, `lamR`, `sigma`, `sig_err` are four parameters of MRME model that describe the duration of moving and resting, mobility parameter σ and measurement error. The initial state of this realization is set as moving by `s0="m"` (and you can also set it to resting by `s0="r"`). The dimension of this generated data is 2 that is specified with `dim = 2`. The columns `X1` and `X2` in `dat` are the two-dimensional location coordinates. The trajectories of this simulated data are shown in the following plot.

```r
tgrid <- seq(0, 10*500, length=500)
set.seed(123)
dat <- rMRME(time = tgrid, lamM = 1, lamR = 0.5, sigma = 1,
             sig_err = 0.01, s0 = "m", dim = 2)
head(dat)
```

```
##       time          X1          X2
## 1  0.00000 0.005615559 -0.01107206
## 2 10.02004 2.070334279  2.05190016
## 3 20.04008 2.740201973  0.45790433
## 4 30.06012 3.175912816 -0.64484454
## 5 40.08016 2.381971954  4.62648177
## 6 50.10020 0.672231889  2.13341037
```



Other models implemented in `smam`

In addition to the MRME, there are four models implemented in the package.

- **Moving-resting (MR) process** (Yan et al. 2014; Pozdnyakov et al. 2019): models animal movement with two states, moving and resting. The transition between two states is modeled by telegraph process. Resting is a motionless state and moving is modeled by Brownian motion. Functions `fitMR()` and `rMR()` provide fitting and simulation from the model, respectively.
- **Brownian motion with measurement error (BMME)** (Pozdnyakov et al. 2014): models animal movement by Brownian motion only with measurement error modelled by added Gaussian noise. Functions `fitBMME()` and `rBMME()` provide fitting and simulation from the model, respectively.

- **Moving-resting-handling (MRH) process** (Pozdnyakov et al. 2020): models animal movement with three states: moving, resting, and handling. Moving state is modeled by Brownian motion. Both resting and handling states are motionless states with duration times modeled by two different exponential distributions. This model assumes animal always switches from a motionless state to the moving state. But when animal switches from the moving state, it may end with resting or handling. Functions `fitMRH()` and `rMRH()` provide fitting and simulation from the model, respectively.
- **Moving-moving (MM) process**(Hu et al. 2021): modified the moving-resting process by replacing the resting state with a second moving state with a relatively lower mobility. These two moving states are assumed to follow two Brownian motions with different mobility parameters. The duration time of these two states are also described by exponential distributions with different rate parameters. Functions `fitMM()` and `rMM()` provide fitting and simulation from the model, respectively.

The `vcov` method has been implemented for each of the five models. See the documentation within the package for more details.

References

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