

Package: RiemBase (via r-universe)

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Type Package

Title Functions and C++ Header Files for Computation on Manifolds

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Description We provide a number of algorithms to estimate fundamental statistics including Fréchet mean and geometric median for manifold-valued data. Also, C++ header files are contained that implement elementary operations on manifolds such as Sphere, Grassmann, and others. See Bhattacharya and Bhattacharya (2012) <[doi:10.1017/CBO9781139094764](https://doi.org/10.1017/CBO9781139094764)> if you are interested in statistics on manifolds, and Absil et al (2007, ISBN:9780691132983) on computational aspects of optimization on matrix manifolds.

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URL <https://github.com/kisungyou/RiemBase>

BugReports <https://github.com/kisungyou/RiemBase/issues>

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RiemBase-package	<i>Functions and C++ Header Files for Computation on Manifolds</i>
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Description

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rbase.curvedist	<i>Distance between Two Curves with Finite Difference Approximation</i>
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Description

Suppose we have two curves $f, g : I \subset \mathbf{R} \rightarrow \mathcal{M}$ evaluated at finite locations $t_0 \leq \dots \leq t_N$, `rbase.curvedist` computes distance between two curves f and g using finite difference approximation with trapezoidal rule. In order to induce no interpolation, two curves should be of same length.

Usage

```
rbase.curvedist(curve1, curve2, t = NULL, type = c("intrinsic", "extrinsic"))
```

Arguments

curve1	a S3 object of <code>riemdata</code> class, whose <code>\$data</code> element is of length N .
curve2	a S3 object of <code>riemdata</code> class, whose <code>\$data</code> element is of length N .
t	a length- N vector of locations. If <code>NULL</code> is given, it uses a equidistant sequence from 1 to N .
type	type of Riemannian distance (" <code>intrinsic</code> " or " <code>extrinsic</code> ").

Value

computed distance.

Examples

```
## Not run:
### Generate two sets of 10 2-frames in R^4 : as grassmann points
ndata = 10
data1 = array(0,c(4,2,ndata))
data2 = array(0,c(4,2,ndata))
for (i in 1:ndata){
  tgt = matrix(rnorm(4*4),nrow=4)
  data1[, , i] = qr.Q(qr(tgt))[,1:2]
}
for (i in 1:ndata){
  tgt = matrix(rnorm(4*5, sd=2),nrow=4)
  data2[, , i] = qr.Q(qr(tgt))[,1:2]
}

gdata1 = riemfactory(data1, name="grassmann") # wrap as 'riemdata' class.
gdata2 = riemfactory(data2, name="grassmann")

rbase.curvedist(gdata1, gdata2)

## End(Not run)
```

rbase.mean

Fréchet Mean of Manifold-valued Data

Description

For manifold-valued data, Fréchet mean is the solution of following cost function,

$$\min_x \sum_{i=1}^n \rho^2(x, x_i), \quad x \in \mathcal{M}$$

for a given data $\{x_i\}_{i=1}^n$ and $\rho(x, y)$ is the geodesic distance between two points on manifold \mathcal{M} . It uses a gradient descent method with a backtracking search rule for updating.

Usage

```
rbase.mean(input, maxiter = 496, eps = 1e-06, parallel = FALSE)
```

Arguments

input	a S3 object of riemdata class. See riemfactory for more details.
maxiter	maximum number of iterations for gradient descent algorithm.
eps	stopping criterion for the norm of gradient.
parallel	a flag for enabling parallel computation.

Value

a named list containing

x an estimate Fréchet mean.

iteration number of iterations until convergence.

Author(s)

Kisung You

References

Karcher H (1977). “Riemannian center of mass and mollifier smoothing.” *Communications on Pure and Applied Mathematics*, **30**(5), 509–541. ISSN 00103640, 10970312.

Kendall WS (1990). “Probability, Convexity, and Harmonic Maps with Small Image I: Uniqueness and Fine Existence.” *Proceedings of the London Mathematical Society*, **s3-61**(2), 371–406. ISSN 00246115.

Afsari B, Tron R, Vidal R (2013). “On the Convergence of Gradient Descent for Finding the Riemannian Center of Mass.” *SIAM Journal on Control and Optimization*, **51**(3), 2230–2260. ISSN 0363-0129, 1095-7138.

Examples

```
### Generate 100 data points on Sphere S^2 near (0,0,1).
ndata = 100
theta = seq(from=-0.99,to=0.99,length.out=ndata)*pi
tmpx = cos(theta) + rnorm(ndata,sd=0.1)
tmpy = sin(theta) + rnorm(ndata,sd=0.1)

### Wrap it as 'riemdata' class
data = list()
for (i in 1:ndata){
  tgt = c(tmpx[i],tmpy[i],1)
  data[[i]] = tgt/sqrt(sum(tgt^2)) # project onto Sphere
}
data = riemfactory(data, name="sphere")

### Compute Fréchet Mean
out1 = rbase.mean(data)
out2 = rbase.mean(data,parallel=TRUE) # test parallel implementation
```

rbase.median

*Geometric Median of Manifold-valued Data***Description**

For manifold-valued data, geometric median is the solution of following cost function,

$$\min_x \sum_{i=1}^n \rho(x, x_i) = \sum_{i=1}^n \|\log_x(x_i)\|, \quad x \in \mathcal{M}$$

for a given data $\{x_i\}_{i=1}^n$, $\rho(x, y)$ the geodesic distance between two points on manifold \mathcal{M} , and $\|\log_x(y)\|$ a logarithmic mapping onto the tangent space $T_x\mathcal{M}$. Weiszfeld's algorithms is employed.

Usage

```
rbase.median(input, maxiter = 496, eps = 1e-06, parallel = FALSE)
```

Arguments

input	a S3 object of riemdata class. See riemfactory for more details.
maxiter	maximum number of iterations for gradient descent algorithm.
eps	stopping criterion for the norm of gradient.
parallel	a flag for enabling parallel computation.

Value

a named list containing

- x** an estimate geometric median.
- iteration** number of iterations until convergence.

Author(s)

Kisung You

References

Fletcher PT, Venkatasubramanian S, Joshi S (2009). "The geometric median on Riemannian manifolds with application to robust atlas estimation." *NeuroImage*, **45**(1), S143–S152. ISSN 10538119.

Aftab K, Hartley R, Trunpf J (2015). "Generalized Weiszfeld Algorithms for Lq Optimization." *IEEE Transactions on Pattern Analysis and Machine Intelligence*, **37**(4), 728–745. ISSN 0162-8828, 2160-9292.

Examples

```

### Generate 100 data points on Sphere S^2 near (0,0,1).
ndata = 100
theta = seq(from=-0.99,to=0.99,length.out=ndata)*pi
tmpx = cos(theta) + rnorm(ndata,sd=0.1)
tmpy = sin(theta) + rnorm(ndata,sd=0.1)

### Wrap it as 'riemdata' class
data = list()
for (i in 1:ndata){
  tgt = c(tmpx[i],tmpy[i],1)
  data[[i]] = tgt/sqrt(sum(tgt^2)) # project onto Sphere
}
data = riemfactory(data, name="sphere")

### Compute Geodesic Median
out1 = rbase.median(data)
out2 = rbase.median(data,parallel=TRUE) # test parallel implementation

```

rbase.pdist

Pairwise Geodesic Distances of a Data Set

Description

Geodesic distance $\rho(x, y)$ is the length of (locally) shortest path connecting two points $x, y \in \mathcal{M}$. Some manifolds have closed-form expression, while others need numerical approximation.

Usage

```
rbase.pdist(input, parallel = FALSE)
```

Arguments

input	a S3 object of riemdata class, whose \$data element is of length n . See riemfactory for more details.
parallel	a flag for enabling parallel computation.

Value

an $(n \times n)$ matrix of pairwise distances.

Examples

```

### Generate 10 2-frames in R^4
ndata = 10
data = array(0,c(4,2,ndata))
for (i in 1:ndata){
  tgt = matrix(rnorm(4*4),nrow=4)
  data[, ,i] = qr.Q(qr(tgt))[,1:2]
}

## Compute Pairwise Distances as if for Grassmann and Stiefel Manifold
A = rbase.pdist(riemfactory(data,name="grassmann"))
B = rbase.pdist(riemfactory(data,name="stiefel"))

## Visual Comparison in Two Cases
opar = par(no.readonly=TRUE)
par(mfrow=c(1,2))
image(A, col=gray((0:100)/100), main="Grassmann")
image(B, col=gray((0:100)/100), main="Stiefel")
par(opar)

```

rbase.pdist2

Pairwise Geodesic Distances Between Two Sets of Data

Description

Unlike [rbase.pdist](#), `rbase.pdist2` takes two sets of data $X = \{x_i\}_{i=1}^m$ and $Y = \{y_j\}_{j=1}^m$ and compute mn number of pairwise distances for all i and j .

Usage

```
rbase.pdist2(input1, input2, parallel = FALSE)
```

Arguments

<code>input1</code>	a S3 object of <code>riemdata</code> class, whose <code>\$data</code> element is of length m .
<code>input2</code>	a S3 object of <code>riemdata</code> class, whose <code>\$data</code> element is of length n .
<code>parallel</code>	a flag for enabling parallel computation.

Value

an $(m \times n)$ matrix of pairwise distances.

Examples

```

### Generate 10 2-frames in R^4 : as grassmann points
ndata = 10
data = array(0,c(4,2,ndata))
for (i in 1:ndata){
  tgt = matrix(rnorm(4*4),nrow=4)
  data[, ,i] = qr.Q(qr(tgt))[,1:2]
}

gdata = riemfactory(data, name="grassmann")

## Compute Pairwise Distances using pdist and pdist2
A = rbase.pdist(gdata)
B = rbase.pdist2(gdata,gdata)

## Visual Comparison in Two Cases
opar = par(no.readonly=TRUE)
par(mfrow=c(1,2), pty="s")
image(A, col=gray((0:100)/100), main="pdist")
image(B, col=gray((0:100)/100), main="pdist2")
par(opar)

```

rbase.robust

Robust Fréchet Mean of Manifold-valued Data

Description

Robust estimator for mean starts from dividing the data $\{x_i\}_{i=1}^n$ into k equally sized sets. For each subset, it first estimates Fréchet mean. It then follows a step to aggregate k sample means by finding a geometric median.

Usage

```
rbase.robust(input, k = 5, maxiter = 496, eps = 1e-06, parallel = FALSE)
```

Arguments

input	a S3 object of riemdata class. See riemfactory for more details.
k	number of subsets for which the data be divided into.
maxiter	maximum number of iterations for gradient descent algorithm and Weiszfeld algorithm.
eps	stopping criterion for the norm of gradient.
parallel	a flag for enabling parallel computation.

Value

a named list containing

x an estimate geometric median.

iteration number of iterations until convergence.

Author(s)

Kisung You

References

Lerasle M, Oliveira R~I (2011). “Robust empirical mean Estimators.” *ArXiv e-prints*. 1112.3914.

Minsker S (2013). “Geometric median and robust estimation in Banach spaces.” *ArXiv e-prints*. 1308.1334.

Feng J, Xu H, Mannor S (2014). “Distributed Robust Learning.” *ArXiv e-prints*. 1409.5937.

See Also

[rbase.mean](#), [rbase.median](#)

Examples

```
### Generate 100 data points on Sphere  $S^2$  near  $(0,0,1)$ .
ndata = 100
theta = seq(from=-0.99,to=0.99,length.out=ndata)*pi
tmpx = cos(theta) + rnorm(ndata,sd=0.1)
tmpy = sin(theta) + rnorm(ndata,sd=0.1)

### Wrap it as 'riemdata' class
data = list()
for (i in 1:ndata){
  tgt = c(tmpx[i],tmpy[i],1)
  data[[i]] = tgt/sqrt(sum(tgt^2)) # project onto Sphere
}
data = riemfactory(data, name="sphere")

### Compute Robust Fréchet Mean
out1 = rbase.robust(data)
out2 = rbase.robust(data,parallel=TRUE) # test parallel implementation
```

riemfactory

*Prepare a S3 Class Object 'riemdata'***Description**

Most of the functions for RiemBase package require data to be wrapped as a riemdata class. Since manifolds of interests endow data points with specific constraints, the function riemfactory first checks the requirements to characterize the manifold and then wraps the data into riemdata class, which is simply a list of manifold-valued data and the name of manifold. Manifold name input is, fortunately, *case-insensitive*.

Usage

```
riemfactory(
  data,
  name = c("euclidean", "grassmann", "spd", "sphere", "stiefel")
)
```

Arguments

data	data to be wrapped as riemdata class. Following input formats are considered, 2D array an $(m \times p)$ matrix where data are stacked in columns over 2nd dimension. Appropriate for vector-valued Euclidean or Sphere manifold case. 3D array an $(m \times n \times p)$ matrix where data are stacked in slices over 3rd dimension. list unnamed list where each element of the list is a single data point. Sizes of all elements must match.
name	the name of Riemmanian manifold for data to which data belong.

Value

a named riemdata S3 object containing

data a list of manifold-valued data points.

size size of each data matrix.

name name of the manifold of interests.

Examples

```
# Test with Sphere S^2 in R^3 example
## Prepare a matrix and list of 20 samples on S^2
sp.mat = array(0,c(3,20)) # each vector will be recorded as a column
sp.list = list()
for (i in 1:20){
  tgt = rnorm(3) # sample random numbers
  tgt = tgt/sqrt(sum(tgt*tgt)) # normalize
```

```
    sp.mat[,i] = tgt # record it as column vector
    sp.list[[i]] = tgt # record it as an element in a list
}

## wrap it using 'riemfactory'
rsp1 = riemfactory(sp.mat, name="Sphere")
rsp2 = riemfactory(sp.list, name="spHeRe")
```

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